Measuring the repetition of domestic violence and abuse in police data

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Abbreviations

ACPO: Association of Chief Police Officers

ASC: Adult Social Care

BWV: Body Worn Video

CSC: Children's Social Care

CTS: Conflict Tactics Scale

COP: College of Policing

CPS: Crown Prosecution Service

CRN: Crime Reference Number

CSEW: Crime Survey for England and Wales

DVA: Domestic violence and abuse

EBP: Evidence Based Policing

FCR: Force Control Room

FV: Family violence

HMIC: Her Majesty's Inspectorate of Constabulary

HMICFRS: Her Majesty's Inspectorate of Constabulary and Fire and Rescue Services

HOCR: Home Office Counting Rules

IDVA: Independent Domestic Violence Advisor

ILRN: Incident Log Reference Number

IPV: Intimate partner violence

MASH: Multi-Agency Safeguarding Hub

MARAC: Multi-Agency Risk Assessment Conference

NCRS: National Crime Recording Standard

NPCC: National Police Chiefs Council

OIC: Officer in Charge

ONS: Office for National Statistics

PNC: Police National Computer

PND: Police National Database

PRC: Police Recorded Crime

VAW: Violence against women

UK: United Kingdom

Abstract

Domestic violence and abuse (DVA) is repetitious, and much of the demand is attributable to repeat victims and perpetrators. Targeting resources at repetition could be an effective method of reducing demand. Targeting repetition requires accurate information on repeat victims and perpetrators. This thesis uses data from Lancashire Constabulary to investigate: *what data do the police have on DVA; what are the problems with the current structure of police data for measuring DVA repetition; how can police data be improved to measure DVA repetition?*

Analysis of existing police datasets found the data unsuitable for measuring DVA repetition for four key reasons: different units of measurement; inconsistent recording of personal details; misuse of DVA markers; and information lost in free-text. The framework for measuring DVA repetition and assessing police interventions, was derived from the DVA literature. Observations of the response mapped out the complexity and identified relevant data sources. Information from multiple sources was recoded into a new dataset following the measurement framework.

The new dataset estimated that 51% of victims were repeats, compared to 21% in the original crime dataset. A series of analyses were conducted, designed around existing debates in the DVA literature, for instance whether DVA is gendered and escalatory. The analysis demonstrated the potential for police data to measure patterns of DVA repetition, and assess the impact of police action.

The thesis contributes a process map of the police response to DVA; a measurement framework for measuring DVA and assessing police actions; criteria for future police data collection; and a methodology for restructuring police data. Though the outputs are methodological, the thesis is driven by the substantive implications of improved police data on the ability of the police to measure, respond to and reduce DVA. The thesis has implications for police practice, policy, and Criminological theory.

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Declaration

This thesis is the result of my own work and has not been submitted for the award of a higher degree elsewhere.

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1. Introduction

Domestic violence and abuse (hereafter DVA) is a violent crime that has significant physical, mental and fatal consequences for victims (Campbell, 2002; WHO, 2005), their children (UNICEF, 2006; Bragg, 2003) and wider social and economic costs for society (Oliver et al, 2019). According to the Crime Survey for England and Wales (CSEW), an estimated 2.4 million adults in England and Wales experienced DVA between March 2018 – 2019 (ONS, 2019a), 67% of victims were women (ONS, 2019b). DVA is the cause and consequence of inequality, particularly gender and economic inequality (Radford and Stanko, 1991; Fitz-Gibbon et al, 2018). The reduction of DVA therefore requires fundamental societal change to alleviate the forms of inequality that perpetuate violence (Dobash and Dobash, 1979; Walby, 2009), alongside regulation by the state to deter perpetrators (Erez, 2002).

Though the Criminal Justice System (CJS) alone cannot drive the social change needed to reduce violence, and crime more broadly, the CJS has a responsibility to regulate and deter violent crime (Lewis et al, 2001). To fully criminalise violence, including DVA, agents of the CJS such as the police, need to effectively implement the laws that regulate violence (Erez, 2002; Walby, 2009). This includes treating DVA as seriously as other forms of violent crime (Hester and Westmarland, 2006; Fitz-Gibbon et al, 2018) whilst recognising the factors that distinguish DVA from other forms of violent crime and affect the outcomes of CJS interventions, in particular the intimate or familial relationship between victim and perpetrator (Hoyle and Sanders, 2000; Eigenberg et al, 2012).

Traditionally, forms of DVA have been excused from statute law, seen as a private matter and not treated as seriously by the CJS as other forms of violent crime (Stanko, 1995; Eigenberg et al, 1996). In England and Wales, DVA is no longer excused, domestic relations do not receive impunity and the CJS are encouraged to take DVA as seriously as other crime (Fitz-Gibbon et al, 2018). Until the introduction of the 2015 offence of Controlling and Coercive Behaviour (Home Office, 2015), there was no statutory offence of DVA in England and Wales. When events of DVA are reported, recorded and 'crimed' by the police, they are captured under existing criminal offences, such as assault, sexual offences, and homicide. In 2015, it became mandatory for police forces to manually 'flag' offences identified as DVA (Home Office, 2020a), prior to this, it was not possible to identify DVA in police data.

DVA is a crime, and the CJS are obligated to regulate DVA as it does other forms of crime. As agents of the CJS, the police are responsible for enforcing the laws that regulate DVA. The police are often the first point of contact for the victim when DVA is reported to the authorities (Vigurs et al, 2016) thus play a key influential role in the CJS response.

DVA is a growing area of interest for public policy and academic research. This is demonstrated by ongoing developments to policy and legislation, for instance the introduction of the 2015 offence of Controlling and Coercive Behaviour, and more recently in the passing of the new Domestic Abuse Bill 2021 (Home Office, 2020b). The scale of DVA has recently been of enhanced policy and research concern following early evidence from DVA charities and reports from the police that DVA cases were increasing due to the national lockdown measures implemented to tackle the spread of COVID-19 (Women's Aid, 2020; Ivandić and Kirchmaier, 2020). The lockdown created an ideal environment for DVA perpetrators, closed off help-seeking routes to health services and schools, and the psychological and economic consequences are expected to last far beyond lockdown measures, thus a rise in DVA is expected to continue (Stanko et al, 2020).

Within DVA research, there are persistent debates on the causes and characteristics of DVA, and therefore the proposed methods of intervention. Key debates include the breadth of the definition, particularly whether the focus should be on physical violence (Walby and Towers, 2018) or non-physical forms of abuse/coercion (Stark, 2007); the scale of DVA, whether it is increasing or decreasing (Walby, Towers and Francis, 2016); whether DVA is predominantly men against women (Dobash and Dobash, 1979; 2004) or gender symmetrical (Straus, 1979; 1997); whether a series of DVA escalates in frequency and severity over time (Walby and Towers, 2018; Bland and Ariel, 2020), and whether there are multiple forms (Johnson, 2008).

The outputs of DVA research have implications for public policy and prevention, and therefore policing. One example of such influence includes the preference for mandatory arrest policies in the US and UK following the influential Sherman and Berk (1984) study that suggested arrest reduced the likelihood of reoffending, despite later research suggesting arrest may not reduce reoffending for all offenders (Sherman et al, 1992) and may be associated with a range of negative outcomes for victim and offender (Sherman and Harris, 2013; 2015). A more recent example is the introduction of the 2015 offence of Controlling and Coercive Behaviour (Home Office, 2015), which references Stark (2007) in the rationale for the offence.

Central to debates is measurement (Walby and Towers, 2018). To design and implement an effective intervention requires a thorough understanding of DVA, its causes and characteristics (Dobash and Dobash, 1979). To know how much DVA exists, who the victims and perpetrators are, what acts and patterns of behaviour are included requires that DVA is robustly measured (Buzawa and Buzawa, 2003). Different data sources and frameworks for measuring DVA have reached different conclusions (Johnson, 2008; Walby, Walby and Towers, 2018). A complexity to measuring DVA is that it goes against the traditional view that a crime consists of one victim, one perpetrator and one event

(Walby et al, 2017). DVA is repetitive, with multiple events by the same perpetrator against the same victim. Key to the measurement debate has been whether to count repetition as individual events (Walby et al, 2017), or as one course of conduct, as is the approach taken by the 2015 offence of Controlling and Coercive Behaviour (Home Office, 2015). Another central measurement debate concerns the boundaries of the DVA definition, and which acts/behaviours are included and therefore measured. Debates question whether the boundaries should focus on acts of physical violence (Walby and Towers, 2018), or should expand to include broader forms of non-physical abuse (Stark, 2012; Weiner, 2017). The method of measurement has implications for our understanding of the scale and characteristics of DVA and therefore the most effective means for prevention, policy and policing.

The response of police in England and Wales to DVA has been under heightened scrutiny over recent years following an inspection by Her Majesty's Inspectorate of Constabulary (HMIC) (now Her Majesty's Inspectorate of Constabulary and Fire and Rescue Services (HMICFRS)) published in 2014 that stated the police response to DVA was not good enough. The 2014 HMIC inspection stated that police were not prioritising DVA in practice and the response to DVA was weak compared to that of other crime, with alarming weaknesses in core police activities. There has since been a series of inspections, which state the police response is getting better, though concerns remain (HMIC, 2015; HMICFRS, 2017; 2019). In the most recently published inspection, HMICFRS state that though the overall response continues to improve, they had concerns on the ability of police forces to identify and record repeat DVA and the potential impact this has for victims (HMICFRS, 2019). The report states that many forces do not have the process or systems in place to identify repeats, and emphasise that repeat victims must be identified as early as possible to detect patterns of abuse. The report states that there has been an increase in the number of DVA-flagged crimes, which may indicate an improvement in data recording practices, though despite improvement, some forces still did not have a good enough understanding of their demand.

A key challenge within policing is determining how to best allocate sparse resources to meet demand, control crime and reduce harm to victims (Sherman, 1992; den Heyer, 2014). Over the last decade, police forces have been increasingly concerned with demand management and resource allocation following periods of extensive funding cuts by the government (HM Treasury, 2010; Millie and Bullock, 2012) and expanding and changing demand (College of Policing (CoP), 2015a). DVA is high-volume and high-risk demand for police (HMICb, 2014). In the 2014 review, HMIC stated that police forces in England and Wales received a DVA-related call around every 30 seconds. DVA demand differs from other crime demand as DVA is repetitive, thus much of DVA demand on the police is attributable to the same victims and perpetrators. Sherman's (2007) influential concept of the ‘power few’, states that a minority of offenders account for a large amount of police resources and the majority of harm caused to victims. Bland and Ariel (2015) found in police callouts that 2% of dyads accounted for 80% of DVA harm. Bland and Ariel (2020) also estimated that around 25% of victims and perpetrators came to police attention for DVA on multiple occasions. Robinson and Clancy (2020) state that the majority of harm is attributable to a small number of repeat DVA perpetrators, thus identifying these perpetrators for intervention could significantly reduce harm. The first task for police in contributing towards the reduction of DVA is therefore to accurately identify and measure repetition.

The recording and identification of repeat DVA in police data is problematic for many forces. HMIC (2014b) in their initial inspection of the police response found various definitions of a repeat victim within and between forces, and found several forces were unable to identify repeat victims consistently. Furthermore, the inspection found forces were often poorly equipped to identify patterns of behaviour and officers often had little information when attending reported DVA incidents, stating that poor technology and force information systems prevented officers from accessing vital information.

This thesis is predominantly concerned with the methods of police measurement in cases of DVA, in particular the police methods for identifying and measuring DVA repetition that is reported to the police. Though the thesis is largely focused on measurement, the thesis is driven by the implications a more efficient police measurement framework could have on the ability of the police to respond to and prevent DVA, through the identification and targeting of interventions towards repetition. This introductory chapter will briefly outline some of the key theoretical debates, measurement issues and policing developments that are relevant to the thesis, which will be expanded on in the second chapter, the Literature Review. This introductory chapter will then present the research questions and contributions of the thesis.

1.1. Debates in domestic violence and abuse theory

Relevant to both measurement and the policing of DVA are the theories of DVA that underpin existing measurement, policy and intervention. DVA is a form of violent crime, and is therefore relevant to the field of Criminology (Walby et al, 2014). Although a crime, DVA has not traditionally been accounted for within mainstream Criminological theory (Walby et al, 2014). The mainstream theories of crime that founded Criminology largely failed to account for the role of gender inequality in the explanation of crime, and therefore could not explain violence against women (VAW), and consequently DVA (Radford and Stanko, 1991; Walby et al, 2014). The exclusion of VAW from mainstream theories of crime led to the emergence of a separate VAW research field that builds on the gaps of mainstream Criminology, where DVA research tends to sit.

Within the VAW field, there are debates on the nature of DVA, particularly on the extent to which DVA is gendered (Straus, 1979; Dobash and Dobash, 1979), violent (Stark, 2007), escalatory (Bland and Ariel, 2015; Walby and Towers, 2018) and how DVA should be measured (Johnson, 2008; Walby et al, 2016; 2017). These debates are central to the research design of the thesis. Firstly, academic research on DVA influences definitions, legislations and policies that are used by the CJS, specifically the police, which are the focus of this thesis. Secondly, previous research into DVA has demonstrated the implications of using different data sources and measurement frameworks for measuring DVA, which are considered in the research design of this thesis.

1.2. Problems of measurement

1.2.1. Available data sources

There are two main data sources for measuring DVA in England and Wales, Police Recorded Crime (PRC) and the CSEW (Cooper and Obolenskaya, 2021). The CSEW is a victimisation survey of around 40,000 adults and children in England and Wales (Kantar, 2020). The survey asks respondents about their experiences of crime in the last 12 months, though additional self-completion modules include questions on historical experiences of specific crimes, including DVA and serious sexual assault. The survey measures DVA in two ways. The first is the face-to-face questionnaire[1] which divides into two components: the main questionnaire, and the Victim Form. The main questionnaire collects sociodemographic information from all respondents, regardless of whether they report being a victim of crime. The Victim Form collects information only from respondents that state they have been a victim of crime. In the Victim Form, the interviewer asks the respondent about their experience of crime, how many times they were victims of the same or of multiple crimes, and about the relationship between the perpetrator and the respondent. The Victim Form asks how many times an offence occurred, measured as a continuous number between 1 and 97, allowing a measure of frequency. Crimes are defined from the Victim Form using specific CSEW offence codes, which are designed to match police crime codes as closely as possible (Kantar, 2020). The CSEW definition of violence combines six offence codes: serious wounding; other wounding; common assault; attempted assault; serious wounding with a sexual motive; and other wounding with a sexual motive. The ONS definition of violent crime in this measure does not include the sexual

[1] The face-to-face methodology of the CSEW ceased in March 2020 due to the lockdown restrictions implemented to tackle the COVID-19 pandemic and is currently replaced by a telephone survey. Following ethical guidelines, the sensitive questions in the self-completion modules are not included in the telephone survey (ONS, 2021).

offences of rape, attempted rape and indecent assault, due to the low reporting rate of these offences in the face-to-face component of the survey (ONS, 2020a). Wider forms of non-physical abuse or coercion, such as threats, are not included in the CSEW definition of violence.

The second method is the self-completion module, which asks the respondent detailed questions about their experiences of DVA. The definition of DVA in the CSEW self-completion module is based on the Home Office non-statutory definition introduced in England and Wales in 2013[2]:

'Any incident or pattern of incidents of controlling, coercive, threatening behaviour, violence or abuse between those aged 16 or over who are or have been intimate partners or family members regardless of gender or sexuality. The can encompass but is not limited to the following types of abuse:

• psychological

• physical

• sexual

• financial

• emotional'[3]

(Home Office, 2012a: 19).

The self-completion module therefore captures broader range of offences in its measure of DVA than the face-to-face questionnaire. The self-completion module elicits a disclosure rate around four times higher than the face-to-face questionnaire (Walby and Allen, 2004) and is thus a better measure of DVA prevalence, though does not collect information on the number of individual offences experienced, so cannot provide a reliable measure of frequency.

The CSEW is the most reliable measure of crime in England and Wales, and provides more accurate estimates of the prevalence and frequency of DVA than PRC (ONS, 2018a). However, the focus of this thesis is not on the overall prevalence or frequency of DVA in England and Wales. Moreover, the CSEW provides limited information on the police response to reported DVA incidents, nor any outcome of police or agency response with regards to interventions put in place for perpetrator or victim, or on the frequency or severity of subsequent incidents following intervention. This thesis is

[2] The Domestic Abuse Bill 2021 proposes a new statutory definition of domestic abuse (Home Office, 2020e). At the time of writing, the Bill is awaiting Royal Assent.
[3] The CSEW in both the face-to-face and the self-completion modules do not exclude offenders below the age of 16, therefore child to adult violence is included.

concerned with the measurement of DVA by police, and the implications of measurement for understanding DVA that is reported to the police and for assessing the effectiveness of any interventions implemented by the police. The focus is therefore on police data.

1.2.2. Problems of measurement in police data

From the literature, there appears to be three issues identified as impacting the quality of police data and the ability to measure repeat DVA: lack of or ambiguous definition of repeat, poor data recording, and low quality of technology and information systems.

In their initial inspection of the police response to DVA, HMIC (2014b) found a lack of a clear and consistent definition of a repeat within and between forces. The report states that where a force did have a definition of a repeat, it was often poorly understood and utilised by staff. HMIC emphasise the necessity of defining and thus identifying repetition to uncover patterns of abuse and provide opportunities for intervention. The 2014 HMIC inspection therefore called for unambiguous definitions of terms like 'repeat victim'. The inspection called for the CoP to update their Authorised Professional Practice (APP) and set standards for identifying repeat and vulnerable victims, and repeat and serial perpetrators. HMIC state that the CoP should demonstrate how targeting repetition could prevent further offending.

In response to HMIC, the CoP (2020c) determined it unhelpful to provide fixed definitions of a repeat victim or a repeat perpetrator, as they are likely to have experienced DVA before the first report to the police, thus would already be a repeat. They also expressed concern that a repeat definition could be used to justify resource allocation, which would be unsafe if the definition is based on unreliable information. However, they do provide a definition of a serial perpetrator, intended to assist with perpetrator management processes:

'A serial perpetrator is someone who has been reported to the police as having committed or threatened domestic abuse against two or more victims. This includes current or former intimate partners and family members' (CoP, 2020c: npn).

The definition is therefore focused on the movement of a perpetrator between multiple victims, rather than the number of offences, or events, committed.

Despite the reluctance of the CoP to provide a definition of a repeat victim or perpetrator, the concept and measurement of repetition by the police is required to enforce and record the 2015 offence of Controlling or Coercive Behaviour. In their APP guidance, the CoP (2020c) state the requirements for an offence of Coercive and Controlling Behaviour to be recorded. No specific timeframe or number of events is given, though from the statutory guidance (Home Office, 2015), CoP state that for an offence of controlling or coercive behaviour to be committed, 'the perpetrator **repeatedly or continuously** engages in behaviour towards the victim that is controlling or coercive' (CoP, 2020c: npn). The CoP APP states that whilst there is no specific number of incidents or timeframe specified in the legislation, behaviour that is displayed on only one occasion would not amount to repeated or continuous behaviour; one or two isolated incidents are unlikely to establish a pattern of behaviour; and whilst there is no specific timeframe, incidents that occur years apart are unlikely to establish a pattern.

From 2018/19, the Home Office (2020a) have provided a definition of a repeat victim, with the introduction of a mandatory 'repeat DA' flag. The 'repeat DA' flag requires that police forces attach a second flag, in addition to the existing DVA flag, to notifiable offences that are identified as aligning with the definition of DVA, and the new definition of repeat DVA. The definition and criteria for the repeat flag to be applied is:

'A "repeat victim" is defined as "a second or subsequent report by a victim within a rolling 12 month period".

ALL notifiable crimes that meet the DA definition should have the DA flag applied to them. Where crimes are flagged as Repeat DA then BOTH flags should be applied.' (Home Office, 2020a: 4).

The flag focuses on the number of offences recorded against the victim, regardless of any change in perpetrator. The criteria for repetition in the Controlling or Coercive Behaviour offence focuses on patterns between a specific dyad. There is no definition given by the CoP or Home Office for a repeat perpetrator of DVA. There is arguably therefore no unambiguous definition of a repeat DVA case for the police to consistently identify and record.

The second identified issue with the police measurement of DVA is the accuracy and consistency of data recording practices. The main measure of police demand and activity in England and Wales has been Police Recorded Crime (PRC) (Loveday, 2000). PRC has been criticised as an inefficient measure of crime or police activity due to poor recording practices (Loveday, 2000; Mayhew, 2014) and in 2014, the national distrust of police data led the UK Statistics Authority to remove the national statistics designation from PRC. Police forces collect a lot more data than PRC, on victims, perpetrators and incidents, though inspections have found these data are often lost in complex data recording practices (HMIC, 2017). In their 2014 inspection, HMIC raised concerns over the consistency of information collecting in police investigations of DVA, and concerns over the quality of data held by police forces and their ability to manage this data (HMIC, 2014b). The inspection found some forces were unable to provide a number of DVA cases recorded in a given day. HMIC stated that in some forces the available data on DVA was of very poor quality, and in other forces there was no available data.

Some of the problems identified in data recording and data availability relate to the third measurement issue, which are technology and force information systems that in some forces were found to be poor and outdated. Weak information systems affected the accessibility of important information about victims and perpetrators in several stages of the police response, particularly for call handlers and frontline officers. Poor systems increased the time required for staff to search for information through various systems, preventing information from reaching frontline officers prior to attendance at a reported event.

In the most recent annual inspection of police forces across England and Wales, HMICFRS (2020) found the police service as a whole lacks the infrastructure to maximise the use of the data they collect. A principal reason was the use of multiple unconnected information systems. HMICFRS called for a more systematic way to analyse police data that follows the response from the frontline to the long-term case outcomes for individuals and the wider community. The inspection stated that without the capability to systematically analyse their data, the efficiency of the police response is limited.

These problems of measurement are core to the thesis. The focus of the thesis is the measurement of DVA within police data, and the implications of improved measurement on the ability of police to understand their demand relating to DVA, and to assess the effectiveness of police actions and interventions.

1.3. Developments in police research

Over the last decade, police forces in England and Wales experienced a period of extensive government funding cuts (HM Treasury, 2010), and thus managing demand became evermore crucial (Millie and Bullock, 2012). In addition to the police, other public services including social and welfare services, health and education experienced significant funding cuts (Gill, 2018), which has driven an increase in demand for police to attend social and welfare calls, and the police are struggling to meet this need (CoP, 2015a; Boulton et al, 2017). The struggle of police and other public services to maintain effective service in times of increasing and changing demand is expected to continue for the foreseeable future (Pepper et al, 2020).

One response to finding effective ways of managing decreasing resources and expanding demand has been the endorsement of Evidence Based Policing (EBP) in England and Wales (Neyroud, 2009; Palmer et al, 2019). EBP is a method of determining ‘what works’ in police practice, using empirical research to develop strategies for the police to efficiently respond to demand whilst being cost-effective (Sherman, 1998; 2013). EBP reviews the best evidence available, working with academics and other partners, to challenge and inform policies, practices and decisions (CoP, n.d.(a)). EBP provides the police with the opportunity to develop and evaluate new interventions and ways of working and to tackle existing issues in practice (Pepper et al, 2020). This enables the police to improve their effectiveness, better allocate resources and reduce wasteful and harmful interventions (Pepper et al, 2020).

This thesis both contributes to and partially derives from the EBP agenda and works specifically with an EBP Hub within one English police force, Lancashire Constabulary. With the aim to improve police practice, reduce crime and prevent harm, Lancashire Constabulary have developed a specific EBP Hub that is dedicated to producing, facilitating and managing research. This thesis is an ESRC CASE studentship working with Lancashire Constabulary. The research proposal was designed alongside the Constabulary and in conjunction with the aims of the force. Outputs from the thesis will be distributed directly to the force, in addition to broader outputs, as listed in the contributions of the thesis at the end of this chapter. The next section presents the research questions, followed by the definitions used in the thesis, the contributions of the research, and the structure of the thesis.

1.4. Research questions

The police are increasingly concerned with improving the allocation of resources to meet demand (Palmer et al, 2019). DVA is a high-risk high demand for police forces in England and Wales (HMIC, 2014b). DVA is a crime of repetition (Walby et al, 2017), and a considerable proportion of police demand relating to DVA is attributable to the same perpetrators and victims (Sherman, 2007; Bland and Ariel, 2015). Lancashire Constabulary recognise that much of their demand relating to DVA is repeat demand. To understand what works in reducing DVA repetition requires accurate information on perpetrators, victims, events, and the actions taken by police. HMIC/HMICFRS (2014b; 2015; 2019) inspections of the police in England and Wales have consistently raised concerns over the quality of data recording practices and force information systems for some police forces in England and Wales. The inspections state that poor data and weak systems prevent vital information from reaching frontline response officers, and limit the ability to measure the DVA that comes to police attention, and therefore the ability to assess interventions.

The research questions of the thesis are therefore:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

The first question aims to investigate the data that the police have on *all* cases of DVA, both those that appear to be singular, and repeats. The focus of the latter two questions is specifically on DVA repetition, because much of police DVA demand is attributable to repeats (Bland and Ariel, 2015; Barnham et al, 2017), and patterns of repetition cannot be measured on singular events. Moreover, cases that appear to be singular in a police dataset may represent one time-point within a series of repetition, and other events in the series may not have been reported; may have been reported outside of the study period; or reported in another force area. There is therefore no guarantee that a singular event in a police dataset is actually a singular event, thus singular events are not the focus of the thesis.

1.5. Definitions

The terminology used in the thesis is domestic violence and abuse (DVA). This term aims to align with police forces in England and Wales, which use the term 'domestic abuse', whilst recognising that this term includes both physical violence and non-physical forms of abuse and coercion. This terminology also corresponds to the Home Office terminology in their 2013 definition of domestic violence and abuse.

The thesis uses police data, which relies on the manual identification and flagging of DVA by the police (Home Office, 2020a). The events included in the data and analysis are therefore defined as DVA by the police.

1.6. Contributions of the thesis

The thesis is focused on the improvement of the measurement of DVA within police data. The thesis demonstrates the potential of police data to measure DVA repetition and assess the influence of police actions on patterns of repetition when reconstructed into a measurement framework designed to capture repetition and police actions. The output of the thesis is predominantly methodological. The thesis produces a measurement framework, derived from theory of DVA and knowledge of police data and information systems. The framework is demonstrated as a more effective measure of DVA repetition through the curation of a new dataset, derived from multiple sources of police data taken from the information systems of one police force. A statistical analysis of the curated dataset is treated as a pilot analysis that demonstrates the improvement the framework would make to the capture of DVA repetition and the value of police data in understanding patterns of DVA and the impact of police actions. The analysis of the dataset curated in this thesis estimated that 51% of victims were repeats, compared to 21% in police crime data, therefore demonstrating a more accurate estimate of repetition in the curated dataset than in traditionally available crime data.

Though the output of the thesis is methodological, the motivation of the thesis and the anticipated long-term value of the findings are substantive. If police forces were to improve their measurement of DVA and follow the framework laid out by this thesis, police data would enable the measurement of DVA patterns and assessment of the influence of police actions on DVA repetition that is reported to the police. This would provide the police with insight on their resource use in response to DVA and the impact of their resources use on subsequent patterns of DVA that come to police attention. Furthermore, the reconstruction of police information into the measurement framework demonstrated in this thesis would provide data that can test and challenge existing theories of DVA in academic research.

The main areas of contribution are therefore to EBP, and to DVA theory. To EBP, the thesis provides a measurement framework for capturing and understanding patterns of DVA and police actions, which will allow for more evidence-based decision-making and targeted interventions. The framework promotes evidence-based design of police information systems, to streamline data collecting and sharing, and to design systems with analysis and accessibility, by practitioners as well as analysts and researchers, in mind. To research, the thesis highlights the amount information that is embedded within police data and the value of pulling together multiple forms of police data, including free-text data, to address a research question. The methodology demonstrated in this thesis can be expanded in future research with a larger sample size, more data sources and sophisticated statistical techniques to reconstruct police data into larger datasets for analysis. To theory, the curated dataset and pilot statistical analysis demonstrates that reconstructing police data into the measurement framework suggested by this thesis enables the testing and challenging of existing theories of DVA in academic literature. The implications of testing existing theories are relevant to policy, legislation and future police practice, as susch theories have influence on the polices and legislation that are established to tackle DVA, shown by mandatory arrest policies in the US and UK (Hoyle and Sanders, 2000) and the 2015 offence of Controlling and Coercive Behaviour in England and Wales (Barlow et al, 2020).

1.7. Thesis structure

There are seven chapters in this thesis. Following this Introduction chapter, the chapters are as follows.

Chapter Two: Literature Review. The introductory chapter outlined the key debates within theory of DVA and the implications for policing, the problems of measurement in DVA and policing, and some of the developments to policing that should be acknowledged in the context of the thesis. The Literature Review chapter expands on these areas, highlighting the key topics of debate, including theories on repetition and escalation and the problems of measurement. The chapter then discusses the challenges facing police forces in England and Wales, expanding on the issues of demand and resource allocation, and the need for improved data and measurement in policing. The chapter then brings together DVA and policing to outline the criticisms of the police response to DVA, and to consider the areas of policing and wider CJS that are relevant to the reduction of DVA. The Literature Review concludes with the areas of DVA and policing that should be embedded into a measurement framework for measuring patterns of DVA in police data and evaluating actions taken by the police in response to DVA.

Chapter Three: Methodology. The chapter starts with an overview of the development of the research design, developed alongside discussions with Lancashire Constabulary on their priorities and available data. The chapter then presents the datasets that were available for analysis and the issues within these data that prevented their use for analysis. The chapter then gives an overview of the observations and interactions with the police, and maps out the police response and points of data collection from these observations. The alternative data sources used for the analysis are then described. The chapter then details the methods used in the thesis to measure frequency and severity, followed by the statistical analysis techniques used to test the ability of the curated dataset to examine patterns of repetition and police actions. The chapter also presents the ethical considerations that were addressed at the start of the research. The method of curating the dataset is given in the subsequent Results chapter.

Chapter Four: first Results chapter. The first Results presents the measurement framework derived from the Literature Review and the police observations that was then used to reconstruct multiple sources of police data into a new quantitative dataset. The chapter then gives the method for curating the dataset, including the sampling technique and the method for deriving the required variables. The chapter concludes with a set of criteria for future police data collection.

Chapter Five: second Results chapter. The second Results chapter presents the results of the statistical analyses that were conducted on the curated dataset. The first set of analysis results are descriptive and provide information on the victims, perpetrators and events. The analysis then focuses on examining the frequency and severity patterns of repeat DVA, using latent trajectory analysis. The final section of analysis focuses on the actions taken by the police, using significance tests and regression models to investigate any relationships between the actions taken by the police and DVA repetition in the curated dataset.

Chapter Six: Discussion. The Discussion brings together the empirical findings of the two Results chapters to consider how the results can be interpreted in relation to the aims of the thesis. The Discussion chapter draws on the material of the Literature Review to contextualise the findings.

Chapter Seven: Conclusion. The Conclusion steps back from the detailed empirical findings and looks at the wider implications of the thesis in relation to addressing the research questions. The Conclusion considers how each of the research questions have been addressed, and finally summarises the key contributions of the thesis to theory and evidence-based policing.

2. Literature Review

2.1. Introduction

This thesis is concerned with the measurement of DVA in police data. The focus of the thesis is predominantly methodological, though is underpinned by the substantive implications of improving the police measurement of DVA on the ability to test and challenge existing theories of DVA and to evaluate the influence of police actions on patterns of DVA that come to police attention. The purpose of this Literature Review chapter is not to determine which theories of DVA onset or repetition are the most convincing, or which interventions are the most effective for reducing DVA. The purpose of this Literature Review is to outline the key theories of DVA, the problems of measuring DVA and the areas of policing and the wider CJS that are relevant to the reduction of DVA, to determine the information that should be considered when measuring patterns of DVA and evaluating the effectiveness of police action. The chapter is divided into three sections. The first focuses on theories of DVA and the challenges of measurement. The second focuses on the challenges facing police forces in England and Wales, particularly around demand and measurement. The third section outlines areas of policing and the CJS that are relevant to the reduction of DVA. The sections serve to contextualise the research, outline the existing evidence and to determine what information on DVA and policing should be considered when measuring patterns of DVA and assessing the police response.

The thesis is situated within Criminology, thus the Literature Review starts by positioning DVA within the academic field of Criminology. This first section outlines some of the key Criminological and Sociological theories of DVA. This is followed by a focus on DVA repetition, including theories of escalation. The first section of the Literature Review then outlines some of the key challenges to measuring DVA, including the data sources and required units of measurement. The section finally outlines some of the additional measures that should be considered when examining patterns of DVA and evaluating the police response, recognising the research on sociodemographic factors and experience of DVA, such as gender, ethnicity, health and employment.

The second section of the chapter outlines the challenges faced by police, particularly focusing on their challenge to effectively allocate resources to manage demand, emphasising the need for accurate measurement of repetition to understand demand and aid decision-making in resource allocation. This is followed by a focus on the issues of data and measurement in policing. The third section brings together DVA and policing to situate the thesis in the challenges of the police response to DVA, outlining the issues faced by police forces, and outlining some of the key areas of policing and the wider CJS that are relevant to the reduction of DVA.

The chapter concludes with a summary of the challenges of measuring DVA with police data, and an overview of the information that should be considered to understand patterns of DVA repetition and to evaluate the impact of police action.

2.2. Domestic violence and abuse

2.2.1. Situating domestic violence and abuse within Criminology

DVA involves physical and non-physical forms of violence and abuse between intimate partners and family relations (Home Office, 2012a; 2020a). Most victims are women (Home Office, 2020b). Forms of abuse captured in the new UK definition of DVA include physical or sexual abuse, violent or threatening behaviour, controlling or coercive behaviour, economic abuse, psychological, emotional or other abuse (UK Parliament, 2020). Most behaviours that form the definition of DVA are crimes (Walby et al, 2014) which, in England and Wales, are defined by the law (Home Office, 2020b). DVA is thus relevant to the field of Criminology. However, DVA has been largely unaccounted for in mainstream theories of crime (Radford and Stanko, 1991; Walby et al, 2014). DVA is rooted in forms of inequality, particularly gender inequality, as well as socioeconomic, ethnic, national and religious (Walby, 2009; Fitz-Gibbon et al, 2018). Most mainstream Criminological theories have not accounted for the role of gender inequality in theories of crime, and specifically violent crime, thus have failed to explain DVA (Radford and Stanko, 1991; Walby et al, 2014). Most mainstream Criminological theories have explained crime through inequality, though have focused predominantly on economic inequality, and posited crime as committed by the disadvantaged, therefore failing to explain DVA, where women are both the disadvantaged and the victims (Walby, 2009). This first section of the chapter will situate DVA within the field of Criminology, demonstrating firstly how DVA has been excluded from mainstream theories of crime and consequently emerged as a separate field, though as a crime, DVA is relevant to the field of Criminology.

Many mainstream theories of crime focus on economic inequality, though by focusing on perpetrators and omitting the victims, mainstream theories fail to account for gender inequality, and therefore cannot explain violence against women and DVA. Some of these key theories are summarised here. Merton (1938) explained crime through strain theory, arguing that crime is the result of socially structured inequalities, specifically economic inequalities, which cause structural strain. Merton explains the crime of working-class men, stating that crime occurs when men accept society's culturally defined goals of a successful career, home and material goods but cannot access the legitimate means of a good education and stable employment to achieve the goals. Merton states these men then turn to illegitimate means to achieve the goals. Cohen (1955) expanded Merton's theory to suggest that that structural strain leads to status frustration. Young working-class men who cannot achieve power and status through the socially approved means of educational success and stable employment turn to delinquent subcultures for status. Cloward and Ohlin (1960) further developed Cohen's subculture theory to account for different types of crime and proposed three types of delinquent subculture: criminal, conflict and retreatist. Though Cloward and Ohlin's developments specifically considered causes of violence, their theory focused on violence between young working class men, therefore failing to explain violence by men against women. Later developments to Merton's theory have considered to what extent economic inequality explains crime. Agnew (1992) suggested that the strain itself does not cause crime, but that crime is caused individual's poor coping mechanisms for dealing with the negative emotions caused by strain (e.g. shock, anger, frustration). Lea and Young (1984) argued that it is relative deprivation, the feeling of being deprived in comparison to others, which causes crime rather than poverty itself. Young (1999) argues that as crime within the lower classes appears to rise, the response of society is to create increasingly punitive and exclusionary sanctions on those who commit crime, to symbolically and physically remove them from society. Social exclusion via stigma and labels then encourages individuals to internalise their deviant labels and creates more crime through self-fulfilling prophecy (Merton, 1948) and deviancy amplification (Cohen, 1972).

Becker's (1968) rational choice theory rejects that crime is caused by poor socialisation or subculture and sees crime as a rational choice that people make. A person commits a crime when the benefits of doing so outweigh the perceived risks. Rational choice theory states offenders are no different to non-offenders, though there may be individual differences in how people perceive risk based on their circumstances. Crime occurs when the benefit of committing crime are perceived greater than the benefits of acting within the law. Perceived benefits may be material, or greater power and status. Cohen and Felson's (1979) routine activity theory expands rational choice theory and argues that crime occurs when there are three elements: a motivated offender, a suitable target, and a lack of capable guardian. A capable guardian deters a motivated offender from committing a crime, and may be a witness/bystander, or a security device. Cohen and Felson state that crime is normal and depends on opportunities to commit crime. Crime is structurally significant. Changes in social and economic conditions alter the structural patterns of people's everyday routines and interactions and provide more opportunity for offending. Felson (1993) applied routine activity theory to violence, stating that violence is goal-oriented behaviour. Violence may intend to gain conformity from the victim, to reaffirm status, or to end a dispute. Like other forms of crime, Felson argued that violence occurs when there is an opportunity and a lack of capable guardian to deter a motivated offender.

Rational choice theory influenced the self-control paradigm (Gottfredson and Hirschi, 1990). Self-control is the ability to delay acting on immediate gains in favour of long-term interests. Gottfredson and Hirschi argued that levels of self-control are influenced by family in early life and become stable by age 10. People are not inherently criminal but are socialised to have different levels of self-control. Differences in levels of self-control affect the likelihood of delinquency in childhood and crime in later life. Hirschi and Gottfredson (1983) look at the repetition of offending throughout the life-course, and argue that age is the key correlate of crime. Offending increases until adolescence and then starts to decline in adulthood, this is known as the age/crime curve. They argue that there are relatively stable individual differences in the tendency to engage in crime over an individual's life course and the causes of crime do not change over time. Other demographic and social factors cannot explain crime and do not affect variations in offending behaviour over time. On violence, Gottfredson (2007) argued that there is a robust correlation between misconduct in childhood and violence in later life. Violence may bring some immediate gain such as the ending of a dispute, and those with lower levels of self-control are more likely to use violence. Gottfredson stated that violence correlates with other forms of delinquency and problem behaviours, and offenders do not specialise in violent or non-violent behaviour.

The criminal career paradigm has largely disagreed with Gottfredson and Hirschi's claim that the propensity to offend does not change throughout the life course. A criminal career is the sequence of persistent offending by an individual (Piquero et al, 2003). The criminal career critique of Hirschi and Gottfredson is that the age/crime curve only recognises one pattern of offending over time and does not account for the individual trajectories of different offending groups. The criminal career approach believes that individuals start criminal activity at a certain age, engage in offending in an individual rate, commit various types of crimes and eventually stop. They therefore focus on investigating the onset of offending, the reasons behind persistence in offending, the crime-type mix, whether there is an escalation in offending and when, and why, individuals desist from offending. The literature on criminal careers is relevant to investigating patterns of repeat offending over time, thus is considered specifically in relation to DVA repetition later in this chapter.

These theories represent some of the key criminological explanations of crime, and therefore violence. Most have directly or indirectly associated the causes of crime with economic inequality and focused on crime of young working-class males, explained through real or perceived economic disadvantage. Economic inequality has been used to explain crime through structural strain and relative deprivation (Merton, Cohen, Agnew, Young), greater opportunities for crime (Becker, Felson), and lower levels of self-control (Gottfredson and Hirschi). Criminal career research has suggested the most persistent and chronic offenders are those from multi-problem and broken families (Farrington, 2002). Though inequalities are rooted in classic explanations of crime, gender is largely invisible 'despite gender relations being deeply structured by inequalities' (Walby, Towers and Francis, 2014: 192). These theories have explained crime as caused by those who are disadvantaged in society. Classic theories have focused on offenders and largely ignored victims. By ignoring victims, the gender of crime, and particularly violent crime is invisible (Walby et al, 2014). Classic theories therefore cannot explain violence against women, where women are both the disadvantaged and the victims (Walby, 2009).

2.2.2. Theories of domestic violence and abuse

As mainstream theories of crime have neglected to account for violence against women (VAW), VAW has emerged as a separate field of research (Walby et al, 2014). This section will outline some of the key theories of DVA within the VAW field of research. The theories covered are primarily sociological, as this thesis aligns with the perspective that DVA is a social problem rather than an individual problem as suggested by some theoretical approaches. Individualist approaches for instance see DVA as a problem within the person and treat the individual as the site of change (Scottish Government, n.d.). DVA is understood through the individual, focusing on factors such as characteristics, interests, biology and pathology. A key example is Holtzworth-Munroe and Gregory's (1994) typologies of men who are violent towards their wives, which presents three 'types' of male perpetrators, looking at correlates of psychopathological and personality disorders with the frequency and severity of the violence. The authors suggest that these typologies are considered in the development of perpetrator programmes that are designed to prevent further violent behaviour. Whilst acknowledging that there are multiple approaches to understanding DVA, this thesis aligns with a sociological perspective that crime, including DVA, is a social rather than an individual pathological problem. The following literature is therefore primarily sociological. Within the VAW research field are competing theories of how to conceptualise and measure DVA. Three of the key debates within the field are the extent to which DVA is gendered, violent, and how it measured (Walby et al, 2014).

Straus (1979) theorised DVA as a problem caused by poor conflict management within the family. He states that conflict is inherent to the family, and family members use various tactics to resolve conflict. To investigate the conflict tactics between family members, Straus devised the Conflict Tactics Scales (CTS). The CTS entails a list of individual actions which are used to resolve conflict to generate a score of reasoning, verbal aggression, and violence. The list of actions starts low in coerciveness (e.g. discussing the conflict with a partner) and increases to more coercive and aggressive actions (e.g. slapping and hitting). Straus looked at how often these individual actions were used by members of different family relationships, such as husband to wife, wife to husband, and father to child within a 12-month period to generate CTS scores. Straus claimed that the CTS shows women commit similar rates of violence against their husbands as husbands do to their wives, though acknowledged men were more likely to engage in serious violence and use weapons. Straus argued that the problem for violent families was not the presence of conflict, but the insufficient methods that family members used to resolve conflict.

Dobash and Dobash (1979) disagree with Straus' symmetrical view of gender in DVA. Whilst they accept that all members of the family can use violence, it is not with the same frequency and severity as husbands' physical violence towards wives, nor do other forms of family violence hold the same meaning to wider society. Dobash and Dobash place DVA at the centre of patriarchal ideology. Traditional views of the family that place women as subversive wives less capable than their dominant husbands explain men's violence to intimate partners as an expression of the unequal status between them. In contrast to Straus, Dobash and Dobash (1979) argue that interpersonal violence should not be defined by individual acts of violence but should be understood in its specific social setting and counting the number of individual acts misleadingly conflates persistent brutal violence with isolated minor physical incidents. Dobash and Dobash argue that to stop DVA against women, the hierarchical family structure and subordinate position of women would need to change and the patriarchal domination of society be eradicated. Whilst government and social reforms are useful, they could never solve the problem itself.

Straus (1990) argued against this criticism and stated feminist critics could not accept that women perpetrated physical assault against men at the same rate as men did against women and were denying female violence. Straus (1997) accepted that women's violence against male partners was less likely to cause injury than men's violence against them, but argued that physical assaults by women were still a serious social problem and both forms of violence were acts of coercion. Dobash and Dobash (2004) examined why research into DVA had reached such contradictory conclusions and distinguished two different approaches. Family violence (FV) researchers such as Straus have used act-based approaches, namely CTS, to claim that violence between men and women in family relationships is symmetrical. Alternatively, VAW researchers such as Dobash and Dobash have criticized the act-based FV approach for not considering the wider context of these individual acts and use what they believe is more comprehensive methodology to show that DVA is overwhelmingly perpetrated by men against women.

Dobash and Dobash (2004) state FV research narrowly focusses on individual physical acts whilst VAW research considers the acts, the events, the context and the consequences. Dobash and Dobash argue that FV researchers do not define the problem and provide no concept or meaning to a list of individual physical acts that conflate different forms of violence and aggression with no consideration of their harm or impact. Dobash and Dobash's (2004) research into the experience of violence in couples found that when women did commit violence against male partners, it differed in frequency, intention, injury, and emotional impact. Women rarely used serious violence, and when they did use any violence, it was often in self-defence and had little impact. Research that suggests DVA is gender symmetrical with equal violence between men and women could have adverse influence on the policies and interventions designed to stop DVA, and thus policies and interventions should focus on eliminating male violence against women and providing social and legal services for abused women (Dobash and Dobash, 2004).

Johnson (1995) proposed that the reason for the different conclusions reached by FV and VAW researchers is the use of different methodologies to research different samples to then report on DVA as if they are looking at the same problem. Johnson argued that DVA is not a 'unitary phenomenon' (1995: 292) and that FV and VAW researchers were looking at different types of DVA, and the gender composition varies. Johnson (2006) derived four types of DVA: situational couple violence, intimate terrorism, violent resistance, and mutual violent control, and the conceptual difference between these is the extent to which perpetrators use violence to control their partners. Intimate terrorism, Johnson argues, is what has been the focus of feminist researchers, and is predominantly used by men against women in intimate relationships. In these couples, men control their partners using violence in addition to control tactics such as threats, isolation, and economic subordination. The violence and control in intimate terrorism escalates in frequency and severity over time. Contrarily, situational couple violence has at least one violent partner, but neither individuals will use violence as a means of gaining control of their partner. Johnson argues that situational couple violence is not a 'product of patriarchy' (1995: 285) and instead occurs occasionally when disputes heighten to minor forms of violence that rarely escalates in severity. Johnson argues that situational couple violence is the most common, and is that which has been discussed by FV researchers such as Straus (1979, 1990, 1997). Johnson (2006, 2008) also proposes violent resistance, to describe violence between partners in which one, primarily the man, is violent and controlling to the point where his partner physically fights back, perhaps in self-defence/ retaliation/means of escape. Johnson's fourth type is mutual violent control, the least common, and involves both partners using violence and tactics of control against the other. Johnson (2008) argues that these distinctive types of DVA must be recognised by those developing prevention, as some interventions could be appropriate for one form of DVA but not another. For instance, Johnson states that couples counselling and restorative justice could be viable methods of intervention for cases of situational couple violence, though could pose further danger if used in cases of intimate terrorism.

Stark (2007) proposed that the key issues in DVA research is the focus on physical violence. Stark argues that interventions into DVA have focused too much on specific incidents and assessed severity based on the level of injury or trauma. Stark argues that the focus on physical violence has ignored women's true experience of DVA, in which injury from physical violence encompasses a small part. Stark (2007) calls for a redefinition of DVA to coercive control, stating that a focus on physical violence fails the majority of victimised women. Stark distinguishes from Johnson's 'intimate terrorism' in stating that coercive control over an intimate partner does not need to involve severe violence. Stark (2012) describes coercive control as an ongoing course of conduct in intimate relationships primarily used by male offenders to entrap women, using coercion and control tactics. Coercion is the use of force or threats to gain a particular response, this can include violence, intimidation, stalking, and shaming tactics. Control tactics are used to gain obedience from the partner and can involve methods of isolation, deprivation, exploitation, and regulation. Stark argues that 'coercive control is the most devastating form of abuse as well as the most common' (2012: 212) and feels the behaviours that characterise the coercive control model have not been recognised by DVA interventions. Stark argues that successful intervention for DVA against women would require a complete reframing of DVA to coercive control.

Walby and Towers (2018) unpick the arguments of Johnson (2008) and Stark (2007) to argue that there is no duality to DVA, it is not comprised of two forms; one characterized by coercive control that is gender asymmetrical and the other not characterized by coercive control that is gender symmetrical. Walby and Towers argue that there are not multiple distinct types of DVA, and instead any differences found in the severity of violence likely represent different points of escalation rather than different types of DVA. Walby and Towers propose the new approach of domestic violent crime. Domestic violent crime includes violent crimes perpetrated by intimate partners and family members, it is gender asymmetrical and escalates over time if the victim's resilience is 'compromised because of lack of access to structural, especially economic, resources' (2018: 8). Domestic violent crime does not concentrate on the individual motives of offenders and instead focusses on the link between violence, economy and society. This theory of domestic violent crime extends on previous work (Walby et al, 2016) that found a link between the economic crisis of 2008 and a rise in domestic violent crime, indicating that the economic resilience of women is a causal factor in the frequency of domestic violent crime. This third approach to DVA argues that all forms of violence are coercive and controlling and so there is no use for a separate concept of coercive control. The approach of domestic violent crime emphasizes the need for appropriate measurement and robust methodology to show the true scale of DVA, gendering, repetition and seriousness, as well as its link to structural and economic factors. They state the link between domestic violent crime and economic resilience has implications for policy that could be of more benefit to victims and more practically applicable than current interventions based on typologies of different forms of DVA. Any attempt at effective intervention in the reduction and prevention of DVA requires both a sound understanding of what DVA is and a means of measurement.

2.2.3. Theories of repetition and escalation

The focus of the thesis is the measurement of DVA repetition, as DVA is a repeat crime (Walby et al, 2017). Most theories of DVA agree that DVA is repetitive, though there is disagreement on the extent to which DVA escalates over time. Furthermore, there is a lack of consensus on what escalation means. To consider possible patterns of DVA repetition and escalation, the Criminological literature on criminal careers is considered, followed by studies that specifically examine any evidence of escalation of DVA in police data. Criminal career research looks at patterns of offending over an individual's life course, including the onset, persistence and desistance (Piquero et al, 2003).

This thesis is less focused on the onset of DVA, and looks specifically at patterns of DVA repetition over time, therefore the main interest is in the persistence and desistance of offending. The focus is on the patterns of repetition in police data. Most DVA does not come to the attention of the police (ONS, 2019b). When DVA does come to the attention of the police, the CoP guidance states that the assumption of the police should be that this is not the first time DVA has occurred (CoP, 2020c). The first record of DVA in police data therefore cannot be assumed to be the onset of DVA, or a singular event, instead it is likely to be a point within the pattern of repetition where the DVA has come to the attention of the police. Furthermore, in considering the ability of police data to evaluate the impact of any police action on DVA, the focus of this thesis is on the relationship between police action and DVA repetition, rather than on any relationship between the police and the onset of DVA. This is firstly because, aforementioned, it cannot be assumed that an event of DVA recorded in police data is singular or representative of the onset. Furthermore, this thesis aligns with the position that the prevention of the onset of DVA requires wider social change, and the police alone cannot prevent the onset of DVA. Whilst the thesis focuses on patterns of repetition, and thus the persistence and desistance, or de-escalation, in a criminal career, it is recognised that in criminal career research the concepts of onset and desistance are often connected. Mazerolle and Maahs (2003) for instance note that criminal careers studies traditionally show that early onset is related to frequent, lengthy, serious and violent criminal activity.

Criminal careers research often looks at changes in frequency, defined as persistence or desistance, and the crime-mix of offenders. The concept of escalation can differ. In some cases escalation is referred to as increasing frequency (Sherman et al, 1991), elsewhere as increasing seriousness of offence (Blumstein et al, 1986), and sometimes as both. Piquero et al (2003) distinguish between the terms of acceleration and escalation. Acceleration refers to an increase in the frequency of offending over time, whilst escalation refers only to an increase in severity. Liu et al (2011) use the same conceptualisation. Using a seriousness scale of offences, Liu et al refer to escalation as an increase in the seriousness of offences over time, and distinguish the concept from increases in the frequency of offences. This thesis will use the concept of escalation to refer to both increasing frequency and increasing severity, though will analyse them as separate measures,

An influential area of criminal careers research has been the investigation of the individual and social factors associated with the most persistent offending. One of the most influential criminal career studies is West and Farrington's Cambridge Study in Delinquent Development. The Cambridge study is a longitudinal study of crime and delinquency in 411 young working class males. Patterns of delinquency and criminal behaviour were examined over time and details on factors such as socioeconomic conditions, schooling, friendship, parent-child relationships, extra-curricular activities, school records and criminal records were collected (West and Farrington, 1973). From the first 40 years of study, Farrington (2002) found there was a small group of chronic offenders that accounted for the majority of offending. The most persistent adult offenders came from multi-problem families and had a number of significant childhood factors including impulsivity, low intelligence, family criminality, broken families, and poor parental supervision.

More recently, Harris et al (2011) investigated which factors, taken from attitudinal, relationship and neighbourhood domains had the most explanatory power on the total number of violent events committed by male perpetrators against an intimate partner. The authors combined explanatory variables that had been identified in previous research as relevant to the frequency and severity of intimate partner violence (IPV), including the perpetrator's background characteristics (e.g. years of education, childhood abuse/neglect, employment, substance abuse), antisociality (e.g. scores on Psychopathy Checklist-Revised, symptoms of mental disorder), relationship variables (e.g. length of relationship, number of children, previous children, socioeconomic status) and attitudes and interpersonal values (e.g. antisocial attitudes or values, sexually jealous, condoned, minimised or denied wife assault). The dependent variable was the total number of violent events committed against any current or previous partner. The authors also considered three other dependent variables based on severity. One severity variable was whether the offender had committed at least one offence on the Revised Conflict Tactics Scales (Straus et al, 1996), the second was a score that computed the total amount of injury from a 7-point scale (ranging from no injury to fatality) and the third was the total severity of IPV using the Cormier-Lang scale (Quinsey et al, 2006). Interestingly, the authors found that analyses of these three scales, which focus on the seriousness of offences, gave the same results as using the total number of violent events perpetrated against any current or former partner, thus this first frequency scale was used. The authors found that when all explanatory variables were considered, variables relating to enduring antisocial traits had the greatest significant effect on the long-term perpetration of violence against female partners.

Another key area of criminal careers research has been the investigation of the number of offending trajectories that exist in offending and general populations, and examining whether particular individual and social factors are associated with different trajectories. A pivotal contribution to this field is Moffitt's (1993) 'dual taxonomy' of offenders. Moffitt's taxonomy divides offenders into adolescence-limited and life-course persistent. Adolescence-limited account for the majority of offenders, this offender type refers to individuals whose delinquency is confined to adolescent years of their life. The life-course persistent type is a small group of offenders who commit crime throughout each stage of their life. Moffitt suggests that the causes of each type of offending differ, with the adolescence-limited explainable by factors of development in adolescence, thus indicating that theory for these offenders should focus on desistance. For life course-persistent on the other hand, Moffitt states that theory should focus instead on causal factors of offending in early childhood and seek to explain the continuity of offending throughout the life course. The focus of Moffitt's taxonomy is the frequency of offending over time. Changes in the seriousness of offences over time is not discussed as escalation, but as changes in the types of offences that are available to an individual over time. Moffitt sees changes in the types of offences committed by an individual as aligned with the new social opportunities that we encounter at different points in out lives from lives 'biting and hitting at age 4, shoplifting and truancy at age 10, selling drugs and stealing cars at age 16, robbery and rape age 22, and fraud and child abuse at age 30; the underlying disposition remains the same, but its expression changes form as new social opportunities arise at different points of development' (1993: 679). The life-course-persistent offender is said to be prone to a combination of neuropsychological predispositions and negative environmental conditions such as low socioeconomic status and poor parenting, which contribute to perpetual antisocial behaviour and stable offending behaviour over time. The adolescent-limited offender on the other hand offends with less stability and with less variety.

Mazerolle and Maahs (2003) examine whether Moffitt's typology can be applied to IPV perpetrators. The authors use data from a sample of offenders on parole and their spouses in New York, and examine the relationships between discrete offender groups (high rate compared to low rate offenders). The study also examined a range of factors expected to be associated with IPV based on existing research, such as alcohol/substance abuse, early experiences of violence, psychological and social factors. The analysis sought to determine whether there were any predictors of early onset to delinquency, and whether high-rate, life-course-persistent offenders were more likely to become IPV perpetrators in adulthood. As Moffitt's adolescent-limited offender is less stable in their delinquency and shows less variety in their offending, Mazerolle and Maahs state that adolescent-limited should be less likely than life-course-persistent to assault their partners.

On the number of offending trajectories, Nagin and Land (1993) offer a typology of four trajectories. Nagin and Land used semiparametric Poisson models on a panel dataset following males for more than 20 years. They identified four trajectories based on the frequency of offending. One trajectory represents a non-offending trajectory, the remaining three are offending trajectories. The first is an adolescence-peaked trajectory, where offending peaks during the individual's adolescence and then continues to decline in frequency over time. The second is a low-rate chronic trajectory, referring to individuals that have persistent low-frequency offending throughout the life course. The third is a high-rate chronic trajectory, referring to individuals with persistent high-frequency offending throughout the life course. D'Unger et al (1998) expanded this analysis to investigate the optimal number of offending trajectories in five samples of longitudinal data taken from three separate criminal career studies with different population samples. The results found no clear answer to the optimal number, but it seems to be between four and five, and each sample included an adolescence limited trajectory and a chronic trajectory. D'Unger et al find that the offending trajectories identified in a sample depend on the dependent variable that is measuring the rate of offending (e.g. convictions, arrests, self-reported offending) and the community context of the drawn sample.

In addition to the number of trajectories, criminal career research has investigated whether offenders tend to commit the same type of crime, termed 'specialists', or whether there is versatility in offending, termed 'generalists'. Understanding the crime-mix of offenders is useful for looking at offenders of DVA, and determining whether persistent DVA offenders are specific to DVA only or whether they engage in other forms of offending, and what this means for intervention and prevention (Mazerolle and Maahs, 2003). Blumstein et al (1986) found that offenders tend to commit a range of offences, though most tend to commit to the same crime type. Soothill et al (2008) looked into the changing offending behaviour of young people, focusing specifically at the patterns of 'generalist' or 'specialist' offending. Using a latent class analysis of conviction data over six cohorts between the early 1970s and the late 1990s, Soothill et al found both specialist and generalist offending groups. Specialist offending groups included specific offence categories such as burglary, theft and shoplifting, and dual offence categories where individuals tended to commit offences within the same broader category of offences, such as 'general violence'. The authors also found evidence of versatile offender groups, and overall found young persons were becoming more versatile in their offending patterns.

There has been a subfield of research looking specifically into the crime-mix of sexual violence offenders. Soothill et al (2000) examined the offending patterns of a group of offenders who were convicted in 1973 for a principal sexual offence in England and Wales. A principal sexual offence at the time included indecent assault on a female, indecent assault on a male, indecency between males, and unlawful sexual intercourse with a girl under 16. Only 41 of 7,442 offenders were female, the small meant they were excluded from the study. The largest category of offences was indecent assault against a female. Soothill et al examined whether those who committed sexual offences could be categorised as specialist or generalist offenders. They found no clear distinction between specialist and generalist offenders, sex offenders may be specialists, generalists, or both. Francis et al (2014) examined the offender trajectories for any offenders and sexual offenders. The study found that in the any offending group and the specifically sexual offending group, there were four trajectory patterns. The trajectories between the two groups differed in onset, duration and peak age of offending. Hargreaves and Francis (2014) examined the long-term sexual recidivism risk of juvenile sex offenders to consider whether indefinite placement on the sex offenders' register was proportionate to their risk of reoffending. They found that juvenile sex offenders without an intervening sexual conviction became like non-offenders with regards to risk of sexual conviction after 17 years, thus risk of reconviction declines over time. Hargreaves and Francis recognised that the study did not disaggregate by type of victim, which could affect the patterns found in sex offending trajectories. Though this area of criminal career research has focused on a type of crime that is largely male violence against women, gender is not explicitly recognised as the key component of sexual offending. Furthermore, as recognised by Hargreaves and Francis, the research did not account for the type of victim, and the relationship between victim and perpetrator, thus trajectories specific to DVA could not be accounted for.

Overall, criminal career research suggests that there are multiple offending trajectories that differ in patterns of changing frequency and/or severity over time. These studies indicate that a number individual and social factors influence the most persistent and serious offending, particularly individual traits deemed antisocial, and social factors relating to low socioeconomic status and poor parenting. Although, Soothill et al (2012) have countered this dominant view by demonstrating that there are a number of offending trajectories for middle-class male offenders, and therefore suggest social class may not be a useful explanation of crime.

The following studies focus specifically on the measurement of repeat DVA in police data, focusing on the identification of escalation. As will be discussed later in this chapter, police data are limited in their ability to provide information on crimes, victims and perpetrators (Mayhew, 2014). However, studies have demonstrated that some police data can be informative of the patterns of repetition and risk in the cases of DVA that do come to police attention. Messing's (2007) thesis looked at what risk factors relating to DVA recidivism and escalation were contained in police case files, and investigated whether it is possible to assess the risk of further violence posed by the perpetrator using only information found in the case files. Messing examined 904 police case files in Oakland, California. Messing identified that several risk factors that had previously been linked to DVA recidivism or escalation, such as the use of a weapon and cohabiting outside of marriage, were significantly linked to increased levels of violence. However, Messing also found that some variables that have typically been associated with DVA recidivism and/or escalation, such as separation and threats to kill or injure the victim, were not significantly linked to increased levels of violence in this sample of police case files. The analysis also examined which variables were linked to a greater likelihood of prosecution. Messing found that the strongest indicators of prosecution were variables relating to evidence, in particular the victim's willingness to testify, and the perpetrators involvement with the CJS, for instance the perpetrator being on probation. Messing states that the findings show the capability of police data to produce information relevant to risk, though acknowledges that there are specific limitations to police data.

There are few studies that look specifically at the escalation of DVA in police data in England and Wales. Bland and Ariel (2015) examined five years of police records from Suffolk Constabulary to investigate whether DVA escalated over time in both frequency and seriousness. The study focuses on the dyad as the unit of measurement, and includes both crime and non-crimes. Suffolk Constabulary are unique in storing both crimes and non-crimes on the same system for DVA, which is advantageous for research as both can be analysed together and there is information on victim and perpetrator/suspect for both crimes and non-crimes. The study took a subset of dyads with five or more events in three years. Frequency was measured by looking at the time between each event, severity was measured using an adaptation of the Crime Harm Index (CHI) (Sherman et al, 2016), which applies severity scores to offences proportional to sentence length. Bland and Ariel applied a score of 0.1 to all non-crimes. In victim demographics, there were only slightly more female victims than male in the sample (51% female), though female victims accounted for the majority (77%) of events, indicating that female victims were more likely to experience repeat events. On repeat victimisation, most dyads appeared once in the dataset, with 24% appearing more than once. However, the proportion was higher for victims, with 32% of victims appearing more than once in the data, indicating movement between dyads. On changing frequency, the authors found a significant relationship in the days between calls over time, signifying an increasing rate of frequency as the number of sequential events increases. The study found that the most chronic dyads tended to be unemployed, female victims and white British. On changing severity, the study found slightly significant escalation in severity after the first three recorded events, but most dyads did not have more than three events thus the escalation in severity was relevant only to a small specific subset of dyads. The study found no significant relationship between the rate of events and greater harm. Bland and Ariel did find limitations to the data that added barriers or complexity to facilitating the analysis. The first was the presence of free-text data. As it was difficult to analyse this without extensive coding and reading, the free-text was largely excluded. Secondly, the authors noted that the most significant barrier to meaningful analysis was the lack of a unique identifier for victims. Offenders had unique identifiers, though whilst victims were recorded in each case, they did not have a unique nominal. The authors thus curated a new nominal for victims, using a concatenate of details such as the surname, forename, DOB and address, though this was limited by misspellings and data issues, and required extensive manual editing.

Brimicombe (2016) combined police recorded incidents and crimes from two UK police forces that had been flagged as DVA to examine the escalation of DVA for victims that repeatedly came to police attention. Escalation referred to both the frequency and the severity of events. Frequency was measured as the time between each event, severity was measured using a severity scale developed by Brimicombe and a Police Inspector which allocated a score of between 1 and 12 to each offence type. Non-crimed incidents were all given a score of 1. Brimicombe mapped the individual trajectories for long-term chronic victims (high number of events recorded over an extensive period of time, one example is 42 events over 4.5 years), and for victims of homicide. From observation of the individual trajectories, Brimicombe concluded that there was no evidence of increasing severity over time for repeat victims, though suggested there was some indication of escalating frequency in the trajectories leading to homicide. Like Bland and Ariel, Brimicombe identified a number of data issues that impacted the ability to identify repetition. The issues were largely centred on inconsistent recording and frequent data gaps in personal details, as well as the misspellings and alternative abbreviations of names and addresses when the information was recorded. This required time-consuming reading and formatting to maximise the capture of repetition.

Barnham et al (2017) investigated escalation in IPV using data from Thames Valley Police, looking at frequency and severity. Data were taken on 52,000 offenders identified over five years. Offenders were followed for a 731-day observation period. Frequency was defined as the times between events, and severity was recorded using the CHI scores (Sherman et al, 2016). The analysis observed the crimes committed by offenders following their first event in the data. For repetition, the study found 37% of events were attributable to repeat perpetrators. The remaining events were first time events for repeat perpetrators or first time events of singular perpetrators. On the conditional probability of further offences, the analysis found that for offenders whose first incident was a crime, the probability of a further crime alleged against them generally increased with each further event. On the time between repeat events, the analysis found that frequency got progressively shorter as the number of events increased, indicating a rise in frequency over time. On severity, the analysis found for most offenders, including repeats, there was no evidence of escalating severity over time. Looking at the CHI scores in the following five years of data for the most harmful offenders in the first year of data, the authors found a decrease in the number of perpetrators continuing to commit high harm, thus a general desistance pattern of harm for most offenders. The authors conclude that there was some increasing frequency in both the number of events and rate of events, though no evidence of escalating severity, and that the conditional probability of another events has no effect on the seriousness of the event. They also state even the most harmful perpetrators drop out of police contact in the 1-4 years following their first recorded event. Barnharm et al state these findings are highly relevant to police resource allocation.

2.2.4. Risk factors for domestic violence and abuse

Most sociological theories of DVA agree that the most frequent and severe forms of DVA are concentrated against women by men (Dobash and Dobash, 1979; Stark, 2007; Johnson, 2008; Walby and Towers, 2018) and particularly against women with lower socioeconomic status (Walby et al, 2016). In addition to gender and socioeconomic factors, literature has considered additional DVA risk factors.

The risk factors associated with DVA victimisation do not imply that victims contribute towards their own victimisation, but that certain factors appear to be associated with greater risk of experiencing DVA, or more frequent and severe DVA (Barnish, 2004). One of the most consistent risk factors found to predict DVA victimisation is previous victimisation (Lloyd et al, 1994; Walby and Myhill, 2001). In addition to gender, other demographics factors have been considered. Research has suggested that there are no significant differences in the experience of DVA by ethnic groups (Walby and Allen, 2004). Though no significant differences in DVA victimisation have been found, research suggests that victims in minority ethnic communities may be more vulnerable to escalating DVA due to barriers in seeking help, including prejudice and negative experiences of reporting (Barnish, 2004). Migrant victims of DVA face additional challenges to seeking help such as language barriers and insecure immigration status (Barnish, 2004). It could also be possible that long-standing poor relations between the police and minority ethnic communities in England and Wales (Bowling and Phillips, 2003) prevents victims from reporting DVA to the police.

In addition to demographics, the literature has considered the effects of personal and situational factors. Personal factors include physical and mental health issues, alcohol/substance misuse. Walby and Myhill (2001) found both physical and mental health problems to be a risk factor for DVA victimisation. However, it is difficult to separate cause from consequence, as the onset of physical and mental health issues may have been triggered by DVA victimisation. Lagdon et al (2014) found experiencing IPV increased the mental health harms to victims. Ferrari et al (2016) found high levels of mental health issues, particularly depression, anxiety and PTSD in female victims seeking support from DVA services. Walby and Myhill (2001) suggest that mental and physical health do not cause DVA, but may reduce the capacity of victims to resist DVA. Drug and alcohol use have been found to be higher in DVA victim populations than in non-DVA victim populations (Schumacher and Holt, 2012). As with health issues, it is difficult to distinguish between cause and consequence. Possible associations suggested by the literature include victims using drugs and alcohol to cope with the effects of DVA, and victims with drug and/or alcohol dependency being less likely to cooperate with the police or seek help (Barnish, 2004). One of the key situational factors discussed in the literature is victim separation from the perpetrator (for intimate partner relationships). Research has shown separation from a partner to be a risk factor for the onset or escalation of DVA (Barnish, 2004). Kyriacou et al (1999) found the perpetrator being a former partner of the victim to be a significant risk factor for injurious DVA. Walby and Myhill (2001) found separation from a partner to be a high-risk factor for subsequent DVA. They state that for some separation brings relief to the victim, but for a significant minority separation continues and escalates the violence. One key barrier to successfully leaving the perpetrator is low economic status. Victims with low economic status, measured through factors such as employment, housing and financial stress, lack the economic resources that provide victims with the resilience to leave the perpetrator (Barnish, 2004; Walby and Towers, 2018).

As well as reducing the economic resilience of victims, Walby and Allen (2004) suggested economic inequality affects the perpetrator. Kyriacou et al (1999) found intermittent employment and unemployment to be a risk factor for DVA perpetration. They suggest one reason for the link between low economic status and DVA perpetrators is frustration with their inability to gain status and power through financial resources. As with victims, the literature suggests that the most accurate predictor of a perpetrator committing DVA is previous DVA perpetration, and the more DVA events a perpetrator has committed, the higher the likelihood of a subsequent event (Barnish, 2004). Abramsky et al (2011) found that any previous violence by the perpetrator, DVA or non-DVA, was a significant predictor of DVA perpetration. DVA perpetrators are also more likely than non-perpetrators to have had any prior contact with the police (Barnish, 2004). Personal and situational factors are also considered for perpetrators. Mental health issues have been associated with DVA perpetrators, in particular depression and suicidal thoughts (Barnish, 2004). As with victims, the relationship between mental health and DVA perpetrators is unclear and cause and consequence cannot be easily disentangled. Alcohol/substance misuse have also been found to be risk factors for DVA perpetrators or to be higher in DVA perpetrator populations (Kyriacou et al, 1999; Riggs et al, 2000; Hester, 2009; Abramsky et al, 2011).

The risk factors identified in the literature do not provide causal explanations for DVA, but indicate some specific factors may be more prevalent in DVA populations (Barnish, 2004). The relationships between these factors and DVA perpetration and victimisation are complex and often interact with other factors. Any of these individual risk factors alone therefore cannot explain the onset or repetition of DVA, though may contribute insight into different patterns of DVA frequency and severity and allow for more tailored interventions.

2.2.5. Measuring domestic violence and abuse

DVA is particularly difficult to measure for two reasons. Firstly, most countries do not have one defined crime of DVA. Several crime types capture DVA when the offences that define DVA (e.g. physical violence, harassment, stalking) cross the criminal threshold. Walby et al (2017) note two proposed approaches of resolving this complexity of multiple offence types. The first is to create a new law that counts the repetitive acts within a course of conduct as one crime. This has been the approach taken by England and Wales with the introduction of ‘Controlling or coercive behaviour in an intimate or family relationship’ as a new crime in 2015 which counts a course of repeated actions as one offence (Serious Crime Act, 2015). The second approach would be to measure DVA as a series of separate acts rather than a course of conduct, many of which would cross the criminal threshold. This second approach counts multiple violent crimes rather than merging repetitive events into one offence, recognizes the multiplicity of DVA and requires less legislative revisions (Walby et al, 2017).

The second complexity with measuring DVA is that it is repetitious. Most measurements of violence apply the logic of one victim, one offender, and one event and the unit of measurement to estimate the scale of violence is the number of victims, or the number of crimes. This logic does not apply to DVA, which distinctly involves repeated violent physical events committed by one offender against one victim over time (Walby et al, 2017). The coercive control approach has been to merge multiple events into one offence defined by a course of conduct and so tends to count the number of victims rather than the number of crimes. Walby et al (2016) argue that to capture the repetition and multiplicity of DVA, both crimes and victims need to be counted. Counting only the number of victims discounts most of the violent events experienced by high-frequency victims. When the number of separate violent crimes are included as a unit of measurement, high-frequency victims are made visible and show that the amount of DVA against women is increasing. Walby et al (2017) suggest that to overcome the complications of measuring DVA, measurement should follow the logic of its definition. Measurement of DVA should identify all forms of violence and abuse, the relationship between the victim and perpetrator, the gender of both victim and perpetrator, and the number of repeat events.

Further problems arise from the source of data used. As stated in the Introduction chapter, in England and Wales, there are two main measures of DVA. The first is administrative data, namely PRC and Crime Prosecution Service (CPS) data. The second is data from the CSEW. There are numerous problems in using PRC figures as a measure of crime, one of the most fundamental being that most crime does not come to police attention and as such is never recorded by police (Walby et al, 2017). The CSEW is therefore considered the most reliable measure of crime in England and Wales (ONS, 2018a). The CSEW measures DVA within two sets of questions. The first set of questions in the main questionnaire are asked face-to-face by an interviewer who enters respondent answers into a computer. The second set are within a specific intimate violence module that is self-completed by the respondent, receiving a much higher disclosure rate than the main questionnaire (Walby et al, 2014). Rather than using an adaptation of the CTS as many victimisation surveys have, the CSEW uses crime codes to define and categorise violence. Walby et al (2017) state that crime codes are a more suitable measure of DVA. Crime codes are defined by the act, harm, and intention of the offender, so they capture context of DVA, which is not possible to do with the CTS that only measures the acts and not the harm or intention. The use of crime codes by the CSEW provides comparability to authority measurements of violence, such as PRC. Walby et al (2017) state that administrative data, such as PRC, will never be sufficient for measuring the extent of DVA due to the small proportion of cases that are reported to and recorded by police; they argue that only surveys, such as the CSEW, could possibly measure the extent of DVA with the correct methodology. The latest CSEW estimates suggest that more than four in five victims (83%) do not report domestic violence to the police (ONS, 2018b).

In England and Wales, crimes related to DVA are recorded by police under their specific crime category, such as assault with injury (ONS, 2018a). Crimes that are identified by police as DVA related are now ‘flagged’ so that they can be distinguished and measured. This relies on police officers manually ‘flagging’ offences that they identify as DVA-related (Home Office, 2020a). HMICFRS found issues in the use of flags by police forces, including ‘flags not being used when they should have been; the wrong flags being used; and flags being used without any apparent justification' (2018: 14). It is possible that not all crimes related to DVA are flagged and therefore DVA crime data is an undercount and misrepresentation of DVA that is reported to police. Though an undercount, having information on crimes that have been flagged allows some measurement of the DVA that comes to police attention. In addition to PRC, police forces collect information on DVA incidents that do not cross the crime threshold (ONS, 2018b) and detailed information on cases is often recorded and shared at various stages of the police response. Analyses of these data could be of benefit to policing if made readily accessible (HMIC, 2017). Furthermore, police data is unique in that it has longitudinal data on both the victims and perpetrators that come to police attention. Police data may therefore be able to measure patterns in DVA repetition over time that the CSEW cannot do, as demonstrated by Bland and Ariel (2015), Brimicombe (2016), and Barnham et al (2017). These studies demonstrate that police data can be used to look at patterns of repetition over time, with the caveat that these patterns specifically represent the cases that were reported to and recorded by the police. These studies highlighted further issues in the use of police data to measure repeat DVA, in particular the presence of free-text (Bland and Ariel, 2015), lack of consistent unique identifiers for victims and/or perpetrators (Bland and Ariel, 2015) and inconsistent recording of personal details (Brimicombe, 2016). Further limitations to police data and measurement systems are considered later in this chapter.

2.2.6. Summary of domestic violence and abuse

Most acts that define DVA are a crime, though DVA has been largely invisible in mainstream Criminology (Radford and Stanko, 1991). The study of DVA and VAW has therefore emerged as its own field of research (Walby et al, 2014). Differences in theoretical and methodological approaches to studying DVA have led to conflicting conclusions about its repetition, escalation, gender, measurement, and intervention (Walby and Towers, 2018). To respond and reduce DVA requires understanding of its causes and meaning (Dobash and Dobash, 2004). The lack of consensus in competing theories of DVA could thus affect the effectiveness of subsequent policy developments. Robust methodology and measurement is needed to accurately represent the extent and changing patterns of DVA (Buzawa and Buzawa, 2003; Walby et al, 2016). Police data cannot provide an accurate measure of the levels of DVA in society, but may give insight on the patterns of repeat DVA that are recorded by the police (Brimicombe, 2016). The review of DVA literature raises questions on the nature of DVA that comes to the attention of the police, how can police data be used to measure DVA and what implications could this have for the police and CJS response to DVA. For measuring DVA repetition in police data, the literature on DVA indicates that the data need to have information on both victim and perpetrator to enable the identification of repetition, information on the event including the date and the type of offence, to enable the measurement of frequency and severity, and information on individual and social factors relating to victim and perpetrator, such as gender, relationship, socioeconomic status, physical and mental health issues, alcohol/substance misuse.

2.3. Police and the Criminal Justice System

2.3.1. The position of the CJS in the reduction of crime

Before looking at the police role in the response of DVA, the wider position of the police and CJS in the response to crime is considered. The strategies in which the police and CJS respond to crime have altered over time with political and economic changes to society (Morgan and Newburn, 1997). Up until the 1960s, policing in Britain was local, community focused (Cain, 1973). From the 1970s onwards, the social and economic landscape of society changed: income inequality grew, social classes became increasingly polarised and minority communities became increasingly marginalised (Morgan and Newburn, 1997). As the structure of society changed, crime rose and the CJS was under greater pressure to respond and reduce crime (Morgan and Newburn, 1997). Crime was rising particularly in marginalised areas (Morgan and Newburn, 1997), and as the public's fear of crime grew, there was depleting faith in rehabilitative and welfare-based responses to crime (Newburn, 2007; Buzawa, 2012). The political response to rising crime was more punitive sanctions (Garland, 2001; Newburn, 2007). There was a cultural demand for control focused CJS responses and those who committed crime were labelled as the dangerous 'other' that must be segregated from the rest of society (Garland, 2001). The role of the CJS became focused on managing the risk posed by dangerous individuals and groups (Ericson and Haggerty, 1997). Consequently, CJS policies were exclusionary, making the public feel safer and justifying the state. The social exclusion of those who committed crime was symbolic through stigma and social segregation, and physical through increased incarceration (Garland, 2001; Newburn, 2007).

As policy responses became increasingly penal, police conduct police changed. The police were no longer uniformed members of the public (Manning, 1977), or celebrated national symbols (McLaughlin, 2001) and were increasingly politicised and divided from the public (Morgan and Newburn, 1997). The police became equipped with radios, cars and vans (Gregory, 1968; Holdaway, 1977; 1983) which mobilised officers and took them away from communities. By the 1980s, the relationship between the police and working class and ethnic minority communities was increasingly hostile (Morgan and Newburn, 1997). Part of the Conservative government response was the introduction of the Police and Criminal Evidence Act (PACE) (Home Offce, 2020d), which extended police powers and endorsed the use of arrest, detention and stop and search (Morgan and Newburn, 1997; Reiner, 2010). Ericson and Haggerty (1997) reconceptualised police work as less fixated on crime and deviancy and increasingly centred on risk, surveillance and control.

This punitive turn and penal populism has persisted over recent decades, with a growing prison population, harsher sentences and more restrictive crime control (Newburn, 2007; Jennings et al, 2017). Despite political popularity, punitive policies and approaches to policing have been widely criticised. Punitive strategies have been criticised firstly for causing rather than deterring crime, and for disproportionately targeting disadvantaged and vulnerable communities and exacerbating the effects of social exclusion that lead to crime (Garland, 2001). Research has suggested increased police presence does not deter crime (Kleck and Barnes, 2014), nor do harsher sentences (Darley, 2005; Nagin, 2013), and prison not only does not reduce crime but also increases it (Pritikin, 2008).

Punitive policies and invasive policing have disproportionately disadvantaged already ostracised communities (Garland, 2001). Vitale (2017) recently argued that the strategy of the police and CJS continues to target and criminalise poor and marginalised groups. Vitale argues that the police cause crime through the over-policing of ethnic minority communities, and through punitive responses to social and welfare crises, particularly mental distress and homelessness. The over-policing of ethnic minority communities and their subsequent criminalisation was highlighted in the 1981 Brixton riots (Morgan and Newburn, 1997) and continues to be a persistent problem in policing (Shankley and Williams, 2020). The over-policing and punitive sanctions of ethnic minority communities has recently received heightened international attention. The unlawful killing of George Floyd in May 2020 by police officers in the US sparked global protests (Noor, 2020), led by the Black Lives Matter movement, with one of the key messages of protestors being to 'defund the police' (Elliott-Cooper, 2020).

Responses to the social and welfare crises have been increasingly punitive. Regarding the unemployment crisis, those reliant on welfare support are increasingly under strict surveillance and threat of sanction, leading to further criminalisation of the poor (Dwyer, 2018; Wright et al, 2020). With a lack of well-funded mental health services, the police are increasingly involved in cases of mental distress, where too many result in the arrest and criminalisation of vulnerable individuals (Vitale, 2017). People who are homeless perhaps represent one of the most disadvantaged groups of society, though rather than receiving sufficient housing and welfare support, many have experienced invasive and aggressive policing and surveillance tactics (Vitale, 2017).

Garland (2001) stated that punitive policies were the problem rather than the solution in resolving crime and social policy reform was needed. He argued that policies should address the links between criminal behaviour and social and economic marginalisation. Garland suggested that power and resources be devolved from the state to local levels. Several studies have supported the link between greater welfare support and crime prevention (see Hannon and Defronzo, 1998; Colvin et al, 2002). Vitale (2017) also argues for a complete social reform. He states that power and resources need to be removed from the police and redistributed to welfare and social services. Social policies need to be introduced to address rather than sanction the problem e.g. mental health policies for mental health crises, housing policies for homelessness. The recent calls to defund the police have echoed these arguments and argue for the redistribution of resources from the police to health, social and educational systems, and propose the growth of specific services such as DVA services, social housing and educational maintenance allowance (Elliott-Cooper, 2020). The core of these arguments is that punitive policies, over-policing and criminal justice responses to social and welfare issues exacerbate social exclusion and create crime, though a lack of funding for social and welfare services has pushed these issues into police work (Vitale, 2017).

The role of the police is to reduce and prevent crime (Karn, 2013). Most research on the role of the police in effective crime prevention have endorsed targeting areas where crime is concentrated. Farrell and Pease (1993) argued that the most effective crime reduction effort should concentrate on those who have already been victimised. Farrell and Pease found the risk of repeat victimisation is highest immediately following victimisation. Police resources should therefore be concentrated on victims or areas where crime has just occurred to prevent further crime (Bowers et al, 2004). A small number of victims and offenders account for the majority of crime, thus concentrating police resources on repeat victims or high crime areas should prevent repeat victimisation and offending and reduce the overall level of crime (Pease and Laycock, 1999). In policing, the areas where high crime concentrates are known as 'hot spots', and victims that repeatedly suffer crime as 'hot dots' (Pease and Laycock, 1999). Braga et al (2012) found that concentrating police resources on hot spot areas reduced crime. Grove et al (2012) found that targeting repeat victims of burglary reduced re-victimisation and thus overall levels of crime. Most repeat victimisation research focused on burglary as a crime type to test the preventative effects of greater police resources following victimisation, though some have recognised and tested the preventative effects on DVA and found targeting resources at repeat victims reduces re-victimisation (Lloyd et al, 1994). Though these studies indicate that targeted policing can reduce crime, they state that the police alone cannot completely stop crime, and an effective response requires partnership working with other agencies (Pease and Laycock, 1999; Tilley and Laycock, 2002).

2.3.2. Police demand, risk and resource allocation

The police say they are busier than ever as they try to manage growing demand and expectations under the constraints of reduced resources (NPCC, 2017). This section considers some of the changes and challenges to policing in England and Wales over the last decade, focusing on demand, risk and resource allocation.

2.3.2.1. Demand

Police forces have faced increased scrutiny over recent years with government cuts to central funding forcing the police to justify the scale and importance of the work they do (Smith, 2016). In 2010, the then UK Coalition Government published a Spending Review outlining plans to reduce the deficit (HM Treasury, 2010). Included in these plans was a 20% reduction to central government police funding by the end of the review period in 2014/15. To facilitate the substantial reduction of funding, HM Treasury's review ordered police forces in England and Wales to stop wasteful spending and be more productive. The review ordered all forces to make huge financial savings whilst maintaining effective service and public satisfaction (HMIC, 2012). HMIC (2011a) estimated that the majority of savings would be made through police workforce reductions. To minimise the impact of workforce reduction on levels of crime and public confidence, forces proposed to reduce their workforce in non-frontline roles, to improve the efficiency of their frontline, and to increase the size of the Special Constabulary (HMIC, 2011b).

Following the review period in which police forces were tasked with saving £1.5 million, HM Treasury (2015) claimed that police reforms were working. HM Treasury stated that crime had fallen by over a quarter, the proportion of frontline officers had increased, and victim satisfaction in the police remained strong. This evaluation of police reform was flawed for several reasons; two key problems are its use of PRC and the narrow measurement of police demand.

HM Treasury's (2015) positive view demonstrates the government's narrow perspective of police work. The role of the police is to reduce crime, yet a lack of well-funded public services means the police are now the responders to non-crime social and welfare crises (Vitale, 2017). PRC does not account for the large amount of work done by police that does not constitute the traditional view of police work yet seems to account for the majority of police activity (Boulton et al, 2017). Under the strain of reduced resources and changing police activity, understanding sources of 'demand' is central to police priorities, and police forces still need a better understanding of demand if they are to effectively manage it (HMIC, 2018).

Boulton et al (2017) estimated the demand of one police force using all calls for service made in one year, recognising that PRC represents only a small sample of demand. Boulton et al (2017) found that less than a third (26.89%) of calls related to what they termed 'traditional police business' (2017: 71) such as acquisitive household crimes and sexual offences, and the majority of police resources were absorbed by welfare and 'nuisance' calls. Around one in five calls made to the force over the year were welfare related. The CoP (2015a) used national police data to estimate the demand faced by police forces in England and Wales. Their report aimed to understand why police forces felt busy as ever despite official figures suggesting that crime rates were falling. The CoP report recognised that using PRC as a measure of demand is inaccurate as it does not show the majority of the work that the police do, in particular the proactive and preventative activity that could be vital to crime reduction. The CoP suggest that the police are not meeting their demand because the nature of demand is changing.

The CoP proposed several hypotheses for changing demand. The first is the new and emerging forms of crime that are not accurately captured in current data recording practices, such as cyber-crime, child sexual exploitation, modern slavery and female genital mutilation. Secondly, they suggest that the amount of non-crime demand is increasing, estimating that non-crime incidents accounted for 84% of all calls for service. For some forces, public safety and welfare incidents accounted for the majority of calls, and these incidents were often more complex and resource intensive.

2.3.2.2. Risk and resource allocation

Much of the concern on police demand has been in the context of austerity and focused on the effects of reduced resources, though the police struggle with demand existed before the funding cuts. Flanagan (2008) examined the police at a time when their funding had been increasing. He argued that the public's expectations of the police were expanding and the police role was growing with greater complexity making it increasingly difficult for police forces to meet their demand. Flanagan's report (2008) suggested a contributing factor to police inability to manage demand was risk aversion, stating that police responses were disproportionate to the cases they were investigating. Following the Flanagan report, Heaton (2009) compared the increase of police resources with their growing demand.

Heaton proposed the main reason for the increasing workload was individual reforms implemented by the government or by forces themselves in reaction to high-profile cases. Heaton (2011) framed individual reforms as processes implemented within the police to minimize risk and demonstrate their risk minimising to the government and public. Heaton argued that the police have developed a 'risk-averse organisational culture' (2011: 76). The police rely heavily on public confidence in their ability to fulfil their duties and responsibilities effectively. Heaton states that public confidence in the police had been weakened by high-profile cases and judicial inquiries that publically highlighted police failures, such as the Hillsborough disaster, the Laming Inquiry (Home Office, 2003) and the Bichard Inquiry (Bichard, 2004). An example in DVA policy was the introduction of the Domestic Violence Disclosure Scheme (DVDS) following the high-profile murder of Clare Wood in 2011 (Fitz-

Gibbon and Walklate, 2016). The police reaction to public shaming was to implement processes and procedures that demonstrate they are doing everything possible to minimise risk in every case. Heaton (2011) argued that implementing such a risk minimising standard of response to every incident is unrealistic, particularly with reduced resources. Heaton suggested that the police cannot both meet increasing demand and minimize risks in every case whilst following multiple processes and procedures to do so.

2.3.3. Measuring police work and police data

To measure police work and evaluate whether anything the police do is effective requires data on what the police do. The main form of data used to measure policing is PRC (Loveday, 2000). This section explains why PRC is not an appropriate measure of the crime that comes to police attention, nor of police activity, though recognises there are other sources of police data that may be useful for both policing and research.

PRC is the number of crimes reported to and recorded by the police (ONS, 2018b). The collection and use of PRC has been widely interrogated (UK Statistics Authority, 2014; Mayhew, 2014). PRC does not show a true representation of society's crime levels, and instead represents a social construction of crime (Mayhew, 2014). At the most basic level, for an offence to be included in PRC, it must be reported to or identified by police, and meet the requirements of the National Crime Recording Standard (NCRS). The NCRS was introduced by the Association of Chief Police Officers (ACPO) (now National Police Chiefs Council (NPCC) and implemented across all police forces in 2002, to promote greater consistency between police forces and to encourage a more victim-oriented approach to crime recording (Simmons et al, 2003). The NCRS states 'that an incident will be recorded as a crime (notifiable offence) for 'victim related offences' if, on the balance of probability:

(a) the circumstances of the victims report amount to a crime defined by law (the police will determine this, based on their knowledge of the law and counting rules); and

(b) there is no credible evidence to the contrary immediately available.' (Home Office, 2020a).

PRC is a specific subset of crime, that which is brought to the attention of police, identified as crossing the threshold of a 'notifiable offence' and recorded. Notifiable offences are crimes that police forces have a responsibility to report to the Home Office, 'non-notifiable' offences are recorded by the police but do not need to be reported to the Home Office. Examples of non-notifiable offences include anti-social behaviour and parking offences (ONS, 2021). Offences that are reported but do not cross this threshold and those that do not come to the attention of the police are not represented in PRC, therefore omitting the majority of crime.

Offences that do cross the notifiable threshold are still undercounted, as the counting rules focus on the number of victims rather than the number of crimes, and so multiple crimes committed against one victim by the same offender at the same time are counted as one crime (Mayhew, 2014). The type of crimes represented in PRC vary over time. Firstly, offences that are legally defined as crimes change. New crimes appear in PRC as offences become legally recognised as crimes, for instance the addition of 'revenge porn' as a crime in law in 2015 ('Disclosing private sexual photographs and films with intent to cause distress', Criminal Justice and Courts Act, 2015). Some 'offences' that once would have appeared in PRC but no longer do change as legislation removes their criminal status, for instance 'indecency between men' was fully repealed as a crime in the Sexual Offences Act 2003 but appeared in PRC prior to this. Secondly, in addition to changing legislation, offences that appear in PRC vary with fluctuations in reporting behaviour. The types of offences reported vary over time with external factors (Mayhew, 2014), such as public confidence or trust in the police, the visibility of certain crimes to the public, and media coverage of particular crime (Cohen, 1972).

Mayhew (2014) argues that one of the main challenges to PRC is that the police have produced it. Mayhew states that PRC reflects not the level of crime but the actions taken by people in the CJS. The distrust in the quality of PRC led the UK Statistics Authority to remove the National Statistics designation from statistics based on recorded crime data in 2014, stating that PRC may not be reliable (UK Statistics Authority, 2014). Mayhew (2014) argued that much of the scepticism towards PRC emerged following the increased performance management and target allocation of policing since the 1990s. A New Public Management (NPM) approach to managing public organisations arose in the UK police service in the mid-1990s (Loveday, 2000; Butterfield et al, 2004). New Public Management is an approach to managing public services with the same techniques used in the private sector (Butterfield et al, 2004). These techniques focus on performance rather than procedure, and use methods such as performance reviews and key performance indicators to assess the efficiency of organisations, emphasising the desire for 'value for money' (Butterfield et al, 2004: 397). Butterfield argues that the police service 'is one area of the public sector where the introduction of the NPM poses most dilemmas' (2004: 399). With NPM came more technology to record information, measure performance and increase efficiency. However, as noted by Ericson and Haggerty (1997), rather than reduce the burden of paper as intended, new technology duplicated the effort required (Butterfield et al, 2004). Butterfield et al found that the techniques of NPM encouraged a culture of 'manipulating the system, and evasion' (2004: 412). To comply with performance measures, police sergeants would complete the work that would contribute towards targets, and other tasks would be treated as secondary. Fitzgerald et al (2002) found over-simplified performance targets of the NPM led police to only engage in activities that would help hit targets, depreciating other forms of work and losing public confidence.

NPM performance targets distorted the way police recorded crime (Loveday, 2000). Mayhew (2014) argues that the pressure of crime reduction performance targets incentivized the police to exclude some minor incidents from official figures, and to downgrade the classification of some crimes to non-notifiable offences so that they do not show in PRC. The police have been under pressure for constant improvement, and 'those whose performance is being measured will naturally make their performance look better rather than worse' (Mayhew, 2014: 33). Tactical offence classification and selective crime recording to meet NPM performance targets suggests that PRC is an even greater undercount of the crime, and further shows that PRC is not an accurate representation of true crime levels and instead symbolizes the behaviour and actions taken by those involved in the production of PRC. This is further supported by Mayhew's comparison of PRC counts of crime with the CSEW counts. Mayhew found that in 1991 – 1995, the CSEW count of CSEW offences continued to rise, whilst PRC counts ceased increasing and stabilised, before starting to decline. Mayhew deems it possible that this declining crime rate was not due to a true decline in the levels of crime but instead indicative of selective crime recording by the police to satisfy performance targets. The introduction of the Home Office Counting Rules (HOCR) and the NCRS improved the police crime recording practices. NCRS improves the consistency between CSEW and PRC, though only when police are compliant with the counting rules (Mayhew, 2014).

The number of performance targets set by government has declined over recent years following criticism, though the crime reduction target remains (Mayhew, 2014). Despite less government emphasis on the performance management of the police, the police retain a performance culture. Police forces set their own targets, as do many Police and Crime Commissioner (PCCs) (Mayhew, 2014). The introduction of PCCs in 2012 was central to what the Home Office deemed 'the most radical reforms to policing in at least 50 years' (Home Office, 2010: 2). The Home Office introduced their proposals for PCCs in 2010 within the context of the spending review. PCCs would be directly elected by the public and replace police authorities. Whilst stating that the government would be removing top-down targets, the Home Office (2010) also said that PCCS will hold chief constables account for makings savings and providing value for money, suggesting that performance culture is still encouraged though no longer be functioned by central government. The Home Office report also noted concerns on the manipulation of counting rules by the police to fulfil performance targets, stating that some police officers may have selectively classified offences based on the impact it could have on recorded crime figures and performance measures. Based on these concerns, HMIC (2014a) conducted an inspection on the integrity of PRC.

There is now national interest in the accuracy of police recording of crime, and concerns on the integrity of PRC negatively affects public confidence in the police (HMIC, 2014a). The accurate recording of crime is critical; HMIC states that PRC provides vital information, is widely accessed and used, regularly published, and is important for ensuring that victims have access to the appropriate level of support. Following concerns of perverse recording practices, HMIC's (2014a) inspection investigated the police use of HOCR and conformity to NCRS. From their inspection HMIC (2014a) argued that victims were being let down by forces' failure to record a large proportion of reported incidents. Even when crimes were accurately recorded, some were later being cancelled or 'no-crimed' without justification. HMIC found that police forces had an overall under-recording of 19%, and the worst under-recording was for violent and sexual offences. In the context of austerity, police forces need accurate recording of crime to facilitate best decision-making on their own resource allocation. This information is needed for PCCs, and for the public. Whilst HMIC could not find any hard evidence of perverse or manipulative crime recording in their inspection, some forces did accept that the pressure of performance targets had distorted crime-recording practices in the past. HMIC stated that any remaining pressures to manipulate crime recording to satisfy target measures should be eradicated. The quality of PRC has been a priority for police improvement since the HMIC (2014a) review and its integrity remains a key point of interest for HMIC and the public. HMIC's (2018) annual assessment of the state of policing for 2017 found that whilst the police had improved crime-recording since the integrity inspections, too many forces were still not recording crime accurately.

The data collected by police goes beyond PRC; the police record information on incidents, offenders, victims, local areas, and vulnerable persons; this information could be of vital support to managing public safety and responding to crime effectively, and so needs to be recorded accurately. The fundamental problem with utilising these data is that the means of collection, storing and sharing information within the police are complex. HMIC's (2017) report on the state of policing for 2016 stated that 'the oxygen of effective policing is information' (2017: 28); information is crucial to policing, but redundant if it cannot be readily accessed and used when it is required. HMIC's report emphases the poor use of ICT in the police. HMIC argue that too many police forces have a large number of unique information systems that are only used and understood by a small number of individuals within the force, meaning that vital information is not readily accessible and shareable. HMIC argue that 'until the police service has a fully functional, interoperable system of ICT networks, efficiency and effectiveness are impaired, public safety is imperilled' (2017: 34). To make best use of all data collected by police, a coherent understanding of how each police system works and what information is stored is required. The barriers to accessing the required information within police forces jeopardises public safety, and the current police priority of understanding and addressing 'demand'.

2.3.4. Summary of the police and criminal justice system

The role of the police and the CJS is to reduce crime. Reduced funding to public services, penal populism and social marginalisation have positioned the police as responders to social and welfare crises. This has exaggerated police demand and exacerbated existing problems of social exclusion. On crime prevention, research has focused on targeting police resources at repeat victims and high crime areas and partnership working with other service providers. To evaluate whether anything the police do makes a difference to levels of crime requires police data. PRC is not an effective measure of the crime that comes to police attention nor of police activity. Police forces collect lots of information on events and persons that come to police attention beyond PRC, but these data are often lost within complex systems of data recording and sharing. This section of the literature has raised questions on how actions taken by the police affect levels of crime and perpetuate demand, and how police demand and activity can be measured and evaluated. For measuring DVA repetition in police data, the literature on police data indicates that using multiple data sources beyond PRC may provide the most information on victims, perpetrators and events, and that these data may need to be extracted from multiple information systems.

2.4. Policing domestic violence and abuse

2.4.1. The position of the CJS in the reduction of DVA

This section considers the role of the CJS in the response to DVA, including some actions taken by police. The focus is first on the position of CJS in the wider goal to stop DVA, and then on individual police and agency responses. VAW, including DVA, is the product of social inequalities and the interaction between these inequalities, including gender, economic, ethnic, national and religious (Radford and Stanko, 1991; Walby, 2009). Violence is an instrument of power from the dominant to the less dominant, including from men to women (Dobash and Dobash, 1979). The extent to which violence is deployed is dependent on its regulation by the state and the resilience of individuals to avoid violence (Walby, 2009). DVA was traditionally not regulated by the state (Fitz-Gibbon et al, 2018). DVA was long viewed as occurring in the private sphere thus not the responsibility of the state, and violence deployed by spouses given impunity (Dobash et al, 1992; Stanko, 1995). By excluding VAW from statute law, the state condones it (Walby, 2009). Violence between domestic relations no longer receives impunity and is recognised in statute law (Fitz-Gibbon et al, 2018). However, recognition of DVA in statute law is not enough to regulate or effectively criminalise the violence (Walby, 2009). For violence to be effectively criminalised requires state institutions such as the police, legal practitioners and courts to enforce the law. For DVA to be criminalised requires legal practitioners to use the law and treat DVA as seriously as all other violent crime (Hester and Westmarland, 2006). From the 1980s onwards, there has been increasing policy and pressure for the law and legal practitioners to take DVA as seriously as other violent crime (Walklate, 2008). For policing, this included the rise of pro-arrest policies, largely influenced by Sherman and Berk's (1984) US study of policing and DVA, which suggested arresting the perpetrator may reduce recidivism in DVA. Pro-arrest policies have continued in the US and the UK despite the researchers later demonstrating that the effects of arrest varied on the context of the case and could make the violence worse for the victim in the long-term (Sherman et al, 1992).

Despite the recognition of DVA in statute law and increasing pressure for the police and CJS to effect the law (Walklate, 2008), research and government inspections continue to suggest that the police do not effectively understand nor implement DVA legislation (Bond and Jeffries, 2014; Myhill and Johnson, 2016), or take DVA as seriously as other forms of crime (HMIC, 2014b). The HMIC (2014b) inspection of the police response to DVA found that DVA was a policing priority on paper but not in practice. HMIC found multiple weaknesses in the police response, including poor understandings of the DVA definition, lack of clear leadership, lack of skill, equipment and inability to identify dangerous patterns of behaviour. HMIC deemed the police response as not good enough. A follow up inspection in 2015 found that police understanding and attitudes towards DVA were improving and DVA was an increasing priority, but there were still many improvements to be made and the knowledge, skills and understanding of DVA by officers were mixed. Myhill and Johnson (2016) found police officers often used their discretion to interpret and misinterpret the DVA definition to selectively record, downgrade, or not record DVA events as crimes. More recently, Myhill (2019) found that most (though not all) police officers had positive attitudes towards DVA being a part of police work and took DVA seriously. Although, the working rules of what the police felt were appropriate when responding to DVA cases overrode policy e.g. police officers would use their discretion not to arrest due to a lack of evidence and feeling that the case was not prosecutable, or feeling that arrest was not an appropriate intervention, despite having a pro-arrest policy framework.

The most recent HMICFRS update report following the initial 2014 HMIC inspection found that some areas of the police response were improving, namely the response of call handlers and initial investigation (HMICFRS, 2019). However, the report also found that the number of victims withdrawing their support from the CJS process was increasing, the time to get officers to reported DVA cases was too slow, and there was a lack of understanding of non-physical forms of coercion and abuse.

Whilst research and inspections have indicated that some police officers continue to downgrade DVA events, thus preventing further CJS action being taken (HMIC, 2014b; Myhill and Johnson, 2016), the motivation to do so is not wholly determined by lack of understanding or prioritisation, but also CPS evidence thresholds, though the former interact with the latter (Barlow et al, 2020). Research has continuously found that decisions around arrest are influenced by the available evidence and the perceived likelihood of prosecution (Hoyle and Sanders, 2000; Myhill, 2019). Despite the introduction of Controlling and Coercive Behaviour as an offence and the growing focus on non-physical components of domestic abuse, for police in England and Wales, physical assault and injury are still treated as key indicators of evidence and therefore determinants in whether the police take further action in a case (Robinson et al, 2016; 2018; Barlow et al, 2020). Barlow et al (2020) found police officers often found it difficult to build evidence for a case of coercive control that would pass the CPS threshold. Often police officers were able to collect evidence in cases of physical assault as they could photograph physical injuries, though in cases that did not involve physical violence and injury, officers felt that the available evidence was weak and cases presented as arguments with one word against the other. Barlow et al suggested that these investigative challenges for police in DVA cases that do not present physical injuries could be linked to the outcomes of those cases, for instance whether they lead to prosecution or NFA.

The reduction of DVA cannot be achieved through regulation alone, and relies on the resilience of the victim (Walby, 2009). Walby argues that individuals have greater resilience to violence when they are included in democracy. Social democratic societies have less inequality and less violence, whilst neoliberal societies, such as the UK (Schrecker and Bambra, 2015), have greater inequality, more violence and harsher punitive sanctions for those that break the law, to maintain the order of the state (Walby, 2009). When women and minorities are fully included in the democracy, have access to employment and economic resources, they have greater status, resources and autonomy to escape violence. Most women who report DVA to the police are those with lower social and economic resources (Macqueen and Norris, 2013), whilst middle class women have the resources and autonomy to leave violent perpetrators without the need for the police intervention, and tend to opt for civil rather than criminal interventions (Stanko, 1995). To stop DVA requires social change that fully embeds women and minorities into the democracy, reduces inequality and empowers victims (Dobash and Dobash, 1979; 2004; Stanko, 1995). Legislation condones DVA and legal practitioners such as the police enforce the law, though regulation alone cannot reduce DVA and in lieu of political restructure, additional support services are needed to support and empower victims and provide them with the resilience to leave violence (Stanko, 1995; Hoyle and Sanders, 2000).

Though the CJS alone cannot stop DVA, certain components are valuable to victims and contribute towards challenging the behaviour of perpetrators (Lewis et al, 2001). Hoyle and Sanders (2000) examined how the police and CJS could contribute towards the reduction of DVA. The state condoning of DVA in the UK saw rise to mandatory arrest policies, as well as the introduction of Domestic Violence Officers (DVOs) and Domestic Violence Units (DVUs). Hoyle and Sanders found that there are three police approaches used by the police when responding to DVA. The first is victim choice. Hoyle (1998) found that most DVA victims refused to make a statement or withdrew their statement after reporting DVA to the police. These cases rarely result in prosecution. When victims withdrew, the police and other practitioners were reluctant to go against victim wishes, felt the case was not prosecutable without victim cooperation, and took victim withdrawal as the end of the case (Hoyle and Sanders, 2000). The working rule of the victim choice approach is to follow victim wishes to not pursue the case (Horwitz et al 2011). The second approach is pro-arrest. The pro-arrest (and pro-prosecution) stance is based on the notion that arrest deters DVA (Hoyle and Sanders, 2000), despite evidence showing that arrest does not always deter DVA and for some victims can matters worse (Sherman et al, 1991), lead to dual-arrest (Buzawa, 2012), and have long-term negative outcomes for victims and perpetrators (Sherman and Harris, 2013; 2015). The pro-arrest approach pursues arrest even when this is against the victim's wishes assuming that it is in their best interest, the outcome for the police is the prosecution rather than the reduction of violence (Hoyle and Sanders, 2000; Birdsall et al, 2020). Both the victim choice and the pro-arrest approaches fail to recognise the context in which the victim makes a decision not to support arrest or prosecution. Victims who report DVA want the violence to stop but may not feel able to leave the perpetrator due to being trapped in a controlling relationship, fears of further and worse violence, and a lack of social support and economic resources to leave the relationship (Hoyle and Sanders, 2000; Birdsall et al, 2020). The third approach is victim empowerment.

Hoyle and Sanders interviewed victims who had recent DVA contact with the police. They found that many victims did not want arrest, and most of those that did want arrest did not want prosecution. Often victims contacted the police to diffuse the situation and stop the violence in that moment to allow the victim some space, though did not want to take the case any further, often due to fears of further and worse violence from the perpetrator following CJS intervention. Hoyle and Sanders also interviewed victims who had previously had DVA contact with the police though had no recent reports. For some victims, the violence had continued, and they felt CJS intervention had made no difference in increasing nor reducing the overall DVA between the victim and perpetrator. For some victims, the violence had stopped and the victim had successfully left the perpetrator. In most of these cases, the perpetrator had been prosecuted. However, the researchers found that the key to the cessation of the violence was not the prosecution itself, but the victim's cooperation with the CJS process and commitment to leaving the perpetrator. Hoyle and Sanders suggest that prosecution may only be effective if the victim successfully leaves the perpetrator.

Of all the victims that left the perpetrator in their study, most had the support of a DVO. DVOs provided the victim with emotional and practical support, including advice on criminal and civil proceedings and support to end relationships. DVOs provided intense support for victims when they were at their most vulnerable and enabled them to regain control and leave the perpetrator. DVOs were thus instrumental in empowering victims to leave the perpetrator and supporting them any CJS or civil process. Hoyle and Sanders thus suggest that the most appropriate model for the police in response to DVA is a victim empowerment model. The victim can use the law as a source of power but the CJS alone cannot empower them to leave the perpetrator, and additional support services are needed to provide the victim with control to make decisions on their own safety and leave the perpetrator.

Hoyle and Sanders suggest that the pro-arrest policy is vital and should be used by practitioners to allow the victim time and space to make safety plans. They suggest that perpetrators must be bailed by police with any appropriate conditions to enable the victim more time away from the perpetrator, and a DVO must be put in contact with the victim immediately to assess the needs and take appropriate action as soon as possible. Hoyle and Sanders emphasise that to make the approach possible, support services need to be sufficiently funded. Though they argue this approach should prevent further violence for the victim, it may not change the behaviour of the perpetrator or protect additional victims. Therefore, in addition to mandatory arrest policies and specialist support for victims, there must also be intervention strategies that directly target perpetrators and assist them to stop offending (Hoyle and Sanders, 2000; Hester and Westmarland, 2006). In summary, the contribution of the police and the CJS to the reduction of DVA is to effectively use the law against DVA perpetrators, and to help facilitate immediate contact with specialist DVA officers and services that support and empower victims to leave the perpetrator.

Most forms of DVA are criminalised by the law (Walby et al, 2014). Recent policy attention has focused on what to do with aspects of DVA that are not captured. Though many theories of DVA embed concepts of non-physical coercion or coercive control into their discussion of DVA, only recently have efforts been made to legally recognise these acts and behaviours (Walklate and Fitz-Gibbon, 2019). As stated earlier, recognising violence in statute law symbolically condemns the violence by the state (Walby, 2009; Fitz-Gibbon et al, 2018). Some researchers and practitioners argued that for the harms of non-physical forms of emotional, financial and psychological abuse to be recognised and condemned, a new law was needed (Home Office, 2014b). The government response in England and Wales was to introduce the new law of Controlling and Coercive Behaviour in an Intimate Relationship (Serious Crime Act, 2015), which criminalises patterns of behaviour. The types of behaviours that may comprise a pattern of behaviour include isolation, deprivation, monitoring a person, enforcing degrading, humiliating or dehumanising rules, controlling a person's activity, financial abuse, threats to hurt or kill, assault, criminal damage and rape (Home Office, 2015). Though the intention of the new law is to condemn and criminalise harmful behaviour, some responses have asked whether the introduction of this legislation helps to improve the response to DVA or actually leads to worse outcomes for victims (Walklate and Fitz-Gibbons, 2019). Walklate and Fitz-Gibbons (2019) argue that a new law of Controlling and Coercive Behaviour is not the answer to improving the police and CJS response. The CJS alone is not an effective tool for responding to DVA, and new legislation fails to consider alternatives to the CJS for reducing DVA. Furthermore, they state that legislation is only as effective as those who implement it (see also Weiner, 2017; Burman and Books-Hey, 2018). The police response to DVA had been long-criticised for poor understandings and implementations of policy prior to a new law being introduced. The new law of Controlling and Coercive Behaviour has proved further problematic due to poor officer understandings and enforcement (Robinson et al, 2018). Improving the police and CJS response to DVA should focus on addressing the problems that already exist within the response (Walklate and Fitz-Gibbons, 2019). Furthermore, the concept and law of coercive control provides methodological as well as conceptual issues that affect and can have long-term consequences for victims (Walklate and Fitz-Gibbons, 2019). The concept and law of coercive control is ambiguous, and involves merging multiple offences into one pattern of behaviour. Merging multiple offences into one impedes effective measurement of the repetition and thus amount of DVA, and accurate measurement is required to persuade the government to take any action on DVA (Walby and Towers, 2018). The police and CJS are typically incident-led, meaning that the response looks at the reported event as isolate and focuses on the circumstances of the individual presenting event to determine the action taken, rather than responding in a way that assumes an event is part of a wider pattern (Stark, 2012; Walklate and Fitz-Gibbons, 2019). The police may therefore be more adequate in responding to a definition of DVA that measures individual incidents, rather than a definition that requires the identification and merging of offences into a pattern of behaviour (Walklate and Fitz-Gibbons, 2019).

2.4.2. Police response to domestic violence and abuse in England and Wales

The rest of this section outlines some of the components involved in the current police response to DVA in England and Wales, then focuses on three specific components: risk assessment, safeguarding and positive action. The first stage of the police response to DVA is the report of the incident. The report is often made by the victim or witness, though reports can be made by third parties, such as health services (CoP, 2015b). Call-handlers receiving the report must consider the context of the incident to identify DVA and grade the priority of the police response. CoP guidance states that all incidents of DVA should receive an immediate response. Contextual factors for the call-handler to consider when determining DVA include whether this is the first call out to the address, whether the victim has a MARAC flag on the local system, whether there are any child protection measures, and whether any previous risk assessments have been made and the results of those risk assessments. Call-handlers should also perform relevant background checks of both victim and offender, including PNC (Police National Computer) and PND (Police National Database) checks. The PNC is a national database used by all police forces in the UK that stores and shares information on criminal records (ACRO, n.d.). The PND is a system available to all police forces and wider criminal justice agencies in the UK that allows the police to input and share local information and intelligence nationally (CoP, n.d.(b)). On deploying a police response, the call-handler must inform the responding officer(s) of all information they have gathered on the incident. This includes exact details of the incident as reported, whether any children or vulnerable adults are present at the scene, the results of any background checks, and any other factors that could affect the police response, such as the presence of weapons, drugs, or intoxicated persons.

Once a response is deployed, the responding officers have a number of duties. In cases of DVA, the responding officer has a dual role (CoP, 2015b). The first is to safeguard the victim; the responding officer must ensure immediate safety, assess risk and start safety planning. In DVA, a core component of decision making when taking action, particularly when safeguarding the victim, is the risk assessment. The second role of the officer is to identify and investigate any criminal offences and take ‘positive action’. This section will firstly outline the methods of risk assessment used by police forces to respond to DVA and some of the key issues. This is followed by an overview of the safeguarding processes in place between the police and partner agencies in England and Wales, and finally a discussion of ‘positive action’, what this means and whether it is viewed as effective.

2.4.2.1. Risk assessment

In times of reduced resources and risk aversion (Heaton, 2011), risk assessment and management have become a central part of policing. In DVA, risk assessment estimates the risk posed by a perpetrator to a particular victim (CoP, 2015b). The purpose of risk assessment is to identify and target police resources at the most high-risk cases; to improve the protection for victims and families at risk of further violence, and to target interventions (Hoyle, 2008).

In England and Wales, the most commonly used method of risk assessment in DVA is 'structured professional judgement' (CoP, 2015b). Structured professional judgement puts the responsibility of the risk classification in the hands of the assessor, in this case the police officer, though a structured tool of risk factors may guide this judgement. The primary risk assessment is carried out as soon as possible, usually at the scene by the responding officer, and should be continuously reviewed (CoP, 2015b). The risk assessment tool used by police forces is the Domestic Abuse Stalking and Harassment and Honour Based Violence (DASH) Risk Model (Richards, 2009). DASH aims to be a common checklist for all police forces and partner agencies, rolled out to all police forces in 2009. DASH intends to guide an understanding of risk based on indicators perceived to be high-risk for DVA. Guidance states that DASH is not a predictive tool and should only guide professional judgement, with the assessor making the final decision on risk classification. DASH has three risk classifications: standard, medium, and high. Generally, a high-risk classification yields the most active police response (Robinson et al, 2016). To guide the risk decision, DASH asks 27 questions. DASH states that the 27 questions ask about several types of abuse and risk including: coercion, threats and intimidation, physical abuse, sexual abuse, children and pregnancy, and economic abuse. DASH highlights that all questions must be asked at every reported DVA event. If the assessor judges that the victim is at risk, information from the DASH must be shared with relevant agencies that will support the victim (CoP, 2015b).

It is crucial in cases of DVA that those responding to the incident understand the nature of DVA and can identify risk so that victims receive the appropriate support and offenders the suitable intervention. Non-identification or misclassification of risk can prevent victims from receiving the right support and intervention and put victims and others at further risk of harm (Myhill and Johnson, 2016). Risk is subjective, a social construct (Hoyle, 2008), and individual officers have different interpretations of risk in different cases. The introduction of risk assessment methods intended to add structure and greater insight to police response, though the use of risk assessment for DVA has raised concern (Hoyle, 2008). One particular concern is that risk assessment decisions may be influenced by available resources as well as risk. Officers may downgrade risk classification or be reluctant to classify some cases as medium or high-risk as these would require more resources. If available resources override accurate risk assessment, then risk assessment is redundant (Hoyle, 2008).

Recent evaluation of police risk assessment of DVA has looked both at the efficacy of the DASH tool to predict further violence, and the use of the DASH by police. Robinson et al (2016) looked at the interpretation and application of DASH across police forces. Robinson et al found that whilst police and partner agencies were largely in support of risk assessment, the DASH tool was inconsistently applied by frontline officers. DASH forms were sometimes left incomplete, officers would choose to not submit a DASH form, or would omit or change particular questions. In the risk factor questions, police prioritized those relating to criminal offences and physical violence and treated these as the most indicative of high-risk. Robinson et al felt that this reflected a poor understanding of coercive control when assessing the risk posed to victims of DVA. Myhill and Hohl (2016) argue that the identification of coercive control is the most important factor in DVA risk assessment and propose police risk assessment tools should be revised and structured around patterns of coercive control rather than individual violent incidents. Robinson et al (2016) suggest specialists rather than frontline police undertake a more thorough risk assessment.

Almond et al (2017) evaluated the appropriateness of the individual risk factors included within the DASH tool in terms of their individual predictive validity for DVA recidivism. A sample of DASH forms from one police force was followed-up after 12 months to analyse which individual risk factors were associated with violent and non-violent recidivism. 25 of 27 DASH questions were analysed due to the removal of two open-ended questions. From the 25 risk factors, only four were found to be associated with any kind of DVA recidivism: criminal history of the perpetrator, separation or attempted separation from the perpetrator, perpetrator problems with alcohol, and if the victim felt frightened. Only criminal history of the perpetrator and separation from the perpetrator could significantly predict recidivism within 12 months. Some risk factors were found to be significantly associated with whether the recidivism was violent or non-violent. Victim pregnancy and injuries caused by the initial incident were in a significantly high proportion of violent recidivisms, whilst stalking/harassment was in a higher proportion of non-violent recidivisms. Almond et al suggested that further empirical evaluation of DASH and its risk factors and risk classifications are needed, but this analysis suggests certain risk factors could aid police decision making to prevent further violence. McManus et al (2017) focused on the use of DASH to describe child-to-parent DVA and determine whether any risk factors could predict recidivism. The researchers found that only two of the 26 DASH risk factors significantly distinguished between recidivists and non-recidivists. Children being present was predictive of non-recidivism, whilst alcohol was predictive of recidivism. These two risk factors differ to the two risk factors associated with recidivism in Almond et al's (2017) evaluation (criminal history and separation). McManus et al suggest this shows the variation in DVA events and thus further guidance is needed on how risk may present differently when using the DASH tool.

Risk assessment helps the police to direct resources proportionately to victims most likely to be at risk of re-victimisation and target intervention at offenders at most risk of re-offending (Almond et al, 2017). Accurate risk assessment should ensure victims receive the appropriate level of support, and offenders the suitable intervention. The problem is that police risk assessment of DVA is inconsistently applied, police officers have a patchy understanding of DVA and the risks associated, the factors most important in identifying risk have been disputed, and the tool used by the police to assess and manage risk lacks empirical evaluation (Robinson et al, 2016; Almond et al, 2017). If the police are to base their decisions on the outcome of risk assessment, the tool they use needs to be accurate, and police officers need to ensure they understand and use the tool consistently.

2.4.2.2. Safeguarding

Methods of safeguarding have become increasingly multi-agency, and the police are one contributing agency (Shorrock et al, 2020). Two of the key multi-agency frameworks within the response to DVA are MASH and MARAC. The MASH and MARAC processes are summarised here, and considered in their ability to effectively safeguard vulnerable persons, including victims of DVA. A key component to safeguarding in cases of DVA contributor to the multi-agency safeguarding initiatives are Independent Domestic Violence Advisors (IDVAs) (Robinson, 2009). The position of IDVAs is also summarised here.

MASH is a multi-agency information-sharing model. The aim of MASH is to improve the safeguarding of vulnerable people through information sharing processes and quality safeguarding responses (Home Office, 2014a). The key principles for MASH are information sharing, joint decision making and coordinated intervention. Several agencies are involved in the MASH, including the police, local authorities, health and probation. In most local authorities that use the MASH model in England and Wales, the agencies are co-located. Through information sharing, MASH intends to prevent repeat victimisation of vulnerable persons by identifying and managing vulnerability early (Shorrock et al, 2020). The Home Office (2014a) identified partnership working between agencies h as critical for tackling DVA (Home Office, 2014a).

An early evaluation of MASH suggested that the model had increased multi-agency working, improved information sharing between agencies and had sped up the time taken between referral and decision-making, thus facilitating faster responses and earlier intervention (Crockett et al, 2013). However, recent research has suggested that the demand placed on MASH is preventing them from working effectively. Shorrock et al (2019) examined the characteristics of referrals made to one MASH. There are a list of reasons for a case to be referred to MASH e.g. vulnerable adult, vulnerable child, and DVA. Shorrock et al found the most common reason for a referral was DVA, and most lead referrals were female. When a referral is made, MASH review the case and decide on appropriate information sharing and safeguarding actions. The allocated time given to review a referral was dependent on the risk classification. For high-risk, referrals should be reviewed within four hours, for medium-risk 24 hours, and for standard-risk 72 hours. MASH intends to facilitate response to the higher risk cases as soon as possible. However, Shorrock et al found that regardless of the risk classification given, the average referral processing time was 10 days. This finding suggests the resources available to MASH cannot meet their demand, preventing MASH from working effectively and blocking immediate safeguarding. In a follow-up study, Shorrock et al (2020) examined the characteristics of cases repeatedly referred to MASH. The study found that a small number of persons accounted for a large number of referrals. Specific demographic and situational factors significantly increased the risk of a repeat referral, though processes within MASH were also deemed to contribute to the risk of a repeat referral. Shorrock et al found that just under one fifth of repeat referrals were re-referred on the same day as their first referral. Further investigation found this was due to referrals being submitted by the number of perpetrators, rather than the number of victims or events. The number of repeat referrals per victim were therefore being overestimated. Shorrock et al argued that inaccurate recording practices such as this prevent the police from providing accurate information on repeat victims to MASH, and hinders the ability to evaluate the effectiveness of MASH for reducing repeat victimisation. To measure repeat referrals and to evaluate MASH requires improvement of accuracy and consistency in data recording practices.

The second framework, specifically designed for DVA, is MARAC. MARACs are multi-agency meetings where both statutory and voluntary organisations discuss and share their information on high-risk DVA cases (Steel et al, 2011). The organisations involved will vary but tend to include the Police, Probation, health, housing, Independent Domestic Violence Advocates (IDVAS) and other specialist adult and children services. The agencies will share information on cases and set actions to facilitate safeguarding for the victim and any children and reduce the risk of any serious or fatal harm (Home Office, 2014a). Actions may relate to the victim, perpetrator, and children. MARAC and MASH are different though can have overlapping cases and work together. HMIC (2014) stated that police forces need to understand the two and ensure there is no duplication of work. Robinson (2004) conducted a process and outcome evaluation of MARAC. The effectiveness of MARAC was judged on the number of police DVA complaints following MARAC, the number of police DVA call-outs after MARAC, and telephone interviews with victims. Robinson found that most victims (around 60%) had not been re-victimised since the MARAC, suggesting that MARACs had effectively helped DVA victims. Furthermore, the agencies who participated in the MARACs deemed them invaluable. Although MARACs produced a substantial amount of additional work for the agencies, they felt this worthwhile as the process enabled them to help victims more effectively. Robinson's evaluation concluded that MARACs have shown benefits to some victims, though the key barriers to MARACs working effectively were resource and time limitations and lack of victim cooperation.

One of the key contributors to the multi-agency frameworks and component in the wider safeguarding response to DVA is IDVAs. IDVAs are specialist caseworkers trained to work with high-risk DVA victims (Howarth et al, 2009). IDVAs offer short to medium support directly to victims. IDVAs work in partnership with other statutory and voluntary agencies though are independent of any agency. Police and other agencies, including those co-located within MASH, may refer a victim to IDVA. A wide range of tailored support is offered by IDVAs to victims, including support with issues on housing, refuge, health, children's schools and support through the CJS process. IDVAs also contribute to MARAC, representing the voice of the victim. Robinson (2009) found that IDVAs contribution to MARAC was deemed invaluable by MARAC. IDVAs and MARAC cannot be separated as they are both focused on safeguarding the most high-risk DVA victims. Howarth et al (2009) conducted an evaluation of IDVA services and found that IDVAs contributed to reductions in the proportion of victims experiencing severe and multiple forms of abuse. Beyond further victimisation, the evaluation found IDVA services had also helped victims' coping mechanisms and enhanced their social networks. IDVAs had thus had a positive influence on victims' wider well-being. The main piece of feedback from Howarth et al's evaluation is that more IDVAs are needed.

2.4.2.3. Positive action and intervention

Often when a crime is identified, positive action means perpetrator arrest, and officers must justify any decision made to not arrest (CoP, 2015b). The decision to arrest lies in the responding officer's professional judgement. The arrest is the start of the police investigation. The police then gather evidence to build a case against the offender to submit to the Crown Prosecution Service (CPS) (CoP, 2015b). It is common in cases of DVA for the victim to retract their complaint against the offender, and so if enough evidence is gathered and it is deemed appropriate, a prosecution can take place without victim participation (CPS, 2017). CoP (2015b) guidance states that officers should avoid making dual arrests of both parties unless absolutely necessary; officers should consider all circumstances of the incident they are attending to determine the perpetrator and arrest the right person. Following arrest, offenders must be given bail conditions to support the positive action and protect the victim (CoP, 2015b).

The key study that influenced pro-arrest policies in DVA was Sherman and Berk's (1984) experiment on the use of arrest in DVA cases in the Minneapolis Police Department in the US. During the experiment, officers randomly assigned one of three responses to eligible DVA offenders when responding to an incident: arrest, advice, and separation of victim and offender. Following these cases up six months after the intervention, Sherman and Berk proposed that arrest had significantly reduced the likelihood of recidivism compared to the other interventions. These findings were influential on pro-arrest policy in the US (Sherman and Cohn, 1989) and the UK (Hoyle and Sanders, 2000). Sherman et al (1992) later replicated the study with an improved randomization methodology in Milwaukee's Police Department. Sherman et al looked at both prevalence and frequency of subsequent violence following arrest, and looked at the difference in deterrence effects between different social subgroups. If prevalence was looked at alone, findings would suggest a pro-arrest policy, thus Sherman et al emphasise the need to look at frequency of subsequent violence as well as prevalence, stating that frequency is more important. Sherman et al's Milwaukee study found that arrest has no long-term deterrent effect on DVA offenders. Deterrence may occur initially but soon ceases and violence would escalate. The study also found that deterrence effects varied depending on the demographics of the suspect, and society's more marginalized individuals were less likely to be deterred by arrest. Sherman et al suggested that alternative interventions may be needed for different individuals. More recent analysis by the researchers have found long-term associations between arrest of DVA perpetrators at the scene and increased likelihood of the perpetrator later dying by homicide than those who were warned (Sherman and Harris, 2013), and earlier death in victims of DVA where the perpetrator was arrested at the scene rather than warned (Sherman and Harris, 2015). Despite evidence that arrest has variable effects on DVA recidivism, policy in England and Wales continues to promote mandatory arrest policies (Hoyle and Sanders, 2000).

Though arrest is encouraged, if this is not possible there are other forms of 'positive action' that the police can take (CoP, 2015b). These measures can be taken in addition to as well as in place of arrest to increase victim protection. If appropriate, the police can remove the perpetrator from the premises to prevent a breach of the peace, and be told to remain away for a set period of time. This should be followed up by a call or visit from the police to make sure the victim is safe. Short-term protection can be implemented with Domestic Violence Protection Notices (DVPNs) and Domestic Violence Protection Orders (DVPOs) (CoP, 2015b) which prohibit the perpetrator from molesting the victim for a set period. To protect the victim and to remove the perpetrator, the police can issue a DVPN. Within 48 hours, the police should apply for a DVPO to the Magistrate's Court. If the DVPO is granted it will last between 14-28 days. Breaching a DVPO is a civil contempt of court and can result in a fine or up to two month's imprisonment (CoP, 2015b). Early evaluation of DVPOs/DVPNs found they were successfully implemented, though levels of police officer support varied and there remained issues in information sharing from the police to support services (Kelly et al, 2013).

There are a number of emergency injunctions attained at civil court which provide the victim with protection from the perpetrator for a longer period. Non-Molestation Orders can prohibit the perpetrator from using violence, intimidating, harassing, pestering or communicating with the victim, and encouraging others to do the same on their behalf (CoP, 2015b). Occupation Orders manage the perpetrator's attendance at the family home, this can include evicting the offender, preventing them from returning, preventing them from coming within a certain distance of the home, and suspending their rights to occupy or visit (CoP, 2015b). Prohibited Steps Orders prevents threats by a person to remove the child by prohibiting that person from removing the child from the other person. Robinson (2007) argues that civil justice is an important component of a holistic approach to DVA. Robinson's study of civil and criminal remedies for DVA found civil injunctions such as occupation orders and non-molestation orders helped victims to feel safer and in some cases provided a deterrent to further violence, though only when implemented with a police power of arrest, otherwise civil orders were felt to be ineffective.

Following a police response that leads to conviction, one intervention administered by the wider CJS may be to put the offender on a domestic violence perpetrator programme. These programmes are designed specifically to change the behaviour of DVA perpetrators. Programmes vary in the length and frequency of treatment, and may involve a range of mechanisms including cognitive behavioural therapy, counselling, anger/aggression management programmes, drug/alcohol treatment and couple's therapy. The intended impact tends to be prevention and/or reduction of recidivism, measured through victim self-reports, perpetrator self-reports and/or official or police records. In a systematic review of domestic violence perpetrator programmes, Vigurs et al (2016a) found inconclusive evidence of the effectiveness of perpetrator programmes to reduce recidivism, or whether a particular programme was more effective than another. The drop-out rate was high for both perpetrators and victims, and those that did not complete their programmes consistently had higher rates of recidivism than those who completed their programmes.

A recent evaluation of the police response to DVA recognised the efforts of the UK government and criminal justice agencies over recent years to reduce DVA with new policies and procedures but argued they have not been achieving the outcomes they intended. Birdsall et al (2017) argue that policies and procedures implemented such as DVPNs and DVPOs, Domestic Violence Disclosure Scheme (DVDS) (Clare's Law) and Specialist Domestic Violence Courts (SDVC) have helped police and victims. DVPNs and DVPOs have helped police when arrest is not available. DVDS allows the public to request information from the police on whether a person has a history of violence and abuse, to prevent further violence and safeguard potential victims if necessary (Home Office, 2016). SDVC's have seen higher conviction rates and greater levels of victim and public confidence (Birdsall et al, 2017). Though these initiatives have been beneficial, Birdsall et al argued that their effectiveness is constrained by inconsistent interpretation and implementation by responding police officers. Birdsall et al placed the inconsistencies in implementation within poor engagement between police and DVA victims. Difficulties in the officer-victim relationship are said to come from the challenge of the police balancing both roles of safeguarding the victim and building a case against the offender. Birdsall et al state that a more 'radical change' (2017: 82) is required in the efforts of government and policing to improve the response to DVA, and victim awareness and empowerment needs to be at the centre.

2.4.3. Summary of the criminal justice system and domestic violence and abuse

The literature indicates that the police and wider CJS cannot stop DVA alone, though have a role to contribute towards the prevention of DVA through regulation and criminalisation. To prevent DVA requires that regulation by the CJS be combined with additional social and economic support to empower and provide victims with the resilience to leave perpetrators. The police response involves various components and is increasingly multi-agency, contributing towards frameworks such as MASH and MARAC, and working with IDVAs. Evaluations of the response to DVA have largely focused on individual components of the police response, such as risk assessment and arrest, or on the effectiveness of multi-agency frameworks. There has been a lack of research on the impact of police information sharing with other agencies and into these frameworks, on the effectiveness of early stages of the police response such as call-handling, and on the police response as a whole (Schucan-Bird et al, 2016). This section raises questions as to what activities the police undertake when responding to DVA, whether any of these actions make a difference, and how any impact of police actions can be measured. For the measurement of DVA repetition in police data, this section of the literature indicates some of the types of police action that should be recorded with a DVA event to enable evaluation of the impact of different types of police action on patterns of DVA repetition. Such police actions may include risk assessment, arrest, charge referral to MARAC and referral to other agencies.

2.5. Conclusion

This thesis is concerned with the measurement of DVA repetition in police data. The focus is largely methodological, though the anticipated impact is substantive. The thesis believes that an improved measurement framework for collecting and analysing DVA in police data would provide the police and researchers with the ability to evaluate the impact of police actions and subsequently enable the police to make more informed decisions on resource allocation to target interventions and contribute towards the reduction of DVA. There are three research questions:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

The purpose of the Literature Review chapter was to consider the existing literature in relation to both DVA and policing, to outline the key theories of DVA, repetition and escalation, to provide context to police concern with the management with demand and wider challenges facing the police in England and Wales, and to outline some of the actions taken by the police and CJS in response to DVA.

The first section situated DVA in the field of Criminology. As mainstream theories of crime have typically failed to account for gender, they have failed to explain violence against women (VAW), including DVA (Walby, 2009). A specific VAW field of research has therefore built on Criminological theories of crime, to address the gap in mainstream theories of crime and theorise DVA. Within the field of research on DVA are persistent debates on the causes and characteristics, in particular the extent to which DVA is gendered, violent and escalatory. DVA is repetitive (Walby et al, 2017). The criminal careers literature indicates that there are multiple patterns of repeat offending, with Nagin and Land (1993) suggesting that there are three offending trajectories. Studies on the escalation of DVA within police data suggest that DVA may increase in frequency over time, but not in severity (Bland and Ariel, 2015; Brimicombe, 2016). To understand DVA and patterns of repetition requires that DVA is accurately measured (Walby et al, 2017). When data disaggregates by gender and relationship, the gendered nature of DVA is visible (Walby et al, 2017). Additional individual and social factors that may interact with the risk of DVA include mental health problems, alcohol/substance misuse (Barnish, 2004). Most DVA does not come to police attention, thus police data alone cannot measure the true extent of DVA (Walby et al, 2017). However, police data has information on the victims, perpetrators and events that come to police attention (HMIC, 2017), and could thus provide insight into the DVA that comes to police attention.

The second section of the Literature Review considered the position of the police and wider CJS in the reduction of crime, and the challenges currently facing police forces in England and Wales. The literature has shown that the CJS alone cannot stop crime. Crime is rooted in forms of inequality, and thus social change is required to effectively stop crime (Walby, 2009). The role of the CJS and its institutions, such as the police, is to regulate crime and pursue perpetrators, though CJS responses need to be combined with social and welfare institutions to alleviate forms of social exclusion that perpetuate crime. Increased social inequality and reduced government funding for public services over recent years, including the police but also social, health and educational services (HM Treasury, 2010), has led to social and welfare crises coming to the attention of the police rather than to other public services, which are more appropriately suited to addressing these issues (Boulton et al, 2017; Vitale, 2017). From the police perspective, this rising and changing demand has left police forces struggling to meet demand and thus effectively respond to calls for service (NPCC, 2017). Public and academic responses to the police's increasing involvement in social and welfare issues have stated that the police are exacerbating the social inequalities that lead to crime (Garland, 2001; Vitale, 2017). To measure the demand that comes to police attention and consider whether anything the police does makes a difference to the levels of crime requires data on police demand and police activity. The review found that PRC is not an appropriate measure of crime, and is more reflective of police data recording processes (Mayhew, 2014). The police collect data beyond PRC, and the police have information on victims, perpetrators and events. The issue in using this data is that it is often lost within multiple unique force information systems and thus inaccessible to practitioners and researchers (CoP, 2015a; HMIC, 2017).

The final section of the review brought together the findings of the literature on DVA and policing to focus on the police and wider CJS response to DVA. This section firstly focused on the position of the CJS within the overall goal to reduce DVA. DVA is cause and consequence of inequalities, particularly gender and economic inequality. The role of the CJS is to regulate and criminalise DVA but a CJS response alone will not stop DVA (Stanko, 1995; Walby, 2009). To effectively reduce DVA, CJS intervention needs to be combined with specialist social and economic support for victims, which empowers victims and provides them with the resources to leave the perpetrators (Hoyle and Sanders, 2000). The police are one institution of the CJS. The police response to DVA is increasingly multi-agency, and involves information sharing with other agencies to facilitate the safeguarding and interventions (Home Office, 2014a). Evaluations of the police response to DVA have focused on individual components, such as risk assessment and arrest. Evaluations have also focused on the effectiveness of support services such as IDVAs (Robinson, 2009), and multi-agency frameworks (Shorrock et al, 2019; 2020), but there has been a lack of evaluation on the information sharing tasks of the police that can connect the CJS and specialised services' responses (Schucan-Bird et al, 2016). Police data alone cannot state whether DVA has truly stopped following intervention (Walby, 2009), but may be able to measure patterns of frequency and severity in DVA that is repeatedly reported to the police (Brimicombe, 2016).

The literature has identified key features of DVA that should be included in a measurement framework to examine patterns of repeat DVA. This includes victim and perpetrator gender, relationship, the number and frequency of events, the severity of events (measured using offence types and severity scores), and individual and social factors that may interact with risk such as mental health issues, alcohol or substance misuse issues. The third section of literature on the police response identified some police actions that should be included in a measurement framework to enable the evaluation of whether any of those actions make a difference to patterns of DVA. These include risk assessment, arrest and referral to other agencies. The literature on policing recognised that PRC alone is not an effective measure of crime, victims and perpetrators. The police collect lots of data, though often data are spread across multiple information systems in different formats and issues of misspelling and inconsistent recording can prevent the identification of repetition. The literature thus indicates that multiple sources of police data may be required to collate all information on the victims, perpetrators and events of DVA that come to police attention, and that extensive cleaning and formatting may be necessary to ensure the measurement of repetition.

The following chapter presents the methodology used for this thesis to address the research questions, including a review of the considered and selected data sources.

3. Methodology

3.1. Introduction

The thesis is interested in the measurement of DVA in police data, with the view that an improved system of data collection could enable the measurement of repeat DVA patterns and the evaluation of the impact of different types of police action on DVA repetition. The thesis seeks to develop a measurement framework for measuring DVA in police data. Though the focus is methodological, the underlying motivation for improving the measurement of DVA in police data is substantive, to increase understanding of DVA patterns that come to police attention, and to determine the impact of different types of police action on DVA patterns.

The original research proposal intended to collate data from Lancashire Constabulary information systems to investigate patterns of DVA repetition. Statistical analysis would be conducted on the extracted data to examine patterns of repetition and to examine the different types of police actions taken in response to DVA repetition. Embedded within the proposal was recognition of the problems of measurement and police data recording practices, emphasising that the effective targeting of police resources required accurate identification and measurement of DVA. The data available were the information already existing in police information systems. For the project, the researcher discussed the available datasets with police analysts, and extracted four quantitative datasets: crimes, offenders, incidents, and DASH risk assessments. From exploratory analysis of these existing datasets, it became apparent that that data were not suitable for identifying and measuring DVA repetition. The focus of the thesis therefore shifted to place more emphasis on the improvement of the measurement of DVA in police data.

The thesis has three research questions:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

The research questions were addressed using a mixed methods research design. The first phase of the research was a series of overt observations and interactions with the police that examined multiple stages of the police response. The aims of the observations were to gain a more thorough understanding of the police response to DVA and to identify the key points of police action and data collection. Alongside the observations, exploratory statistical analysis was conducted on the existing police datasets (crime, offenders, incidents, DASH). The exploratory analysis determined that the existing datasets were unsuitable for measuring DVA repetition and police action. Observations of the police response demonstrated that there were multiple sources of police data that provide further information on DVA repetition and police action. A new dataset was therefore curated using multiple sources of police data, using information on DVA and policing from the Literature Review and knowledge of police information systems to derive a measurement framework. The final phase of the research design was statistical analyses of the curated dataset that examined patterns of DVA repetition and police action. The aims of the statistical analyses were to test the ability of police data to identify patterns of DVA repetition and police action, and to provide initial insight into the patterns of DVA repetition that came to the attention of Lancashire Constabulary.

This chapter first gives an overview of the existing quantitative datasets that were available and extracted from police information systems. The following section outlines observations of the police response that provided insight into the various stages of the response and points of data collection, which assisted the selection of appropriate data sources to measure DVA repetition and police action. An overview of the selected data sources is provided. The data sources were then reconstructed into a new curated dataset using a measurement framework derived from the literature and insight into the police response and information systems. The measurement framework and method for curating the dataset are presented in the subsequent Results One chapter. This Methodology chapter then presents the statistical analysis techniques used on the curated dataset to measure patterns of DVA repetition and police action.

3.2. Considering the suitability of existing police datasets

The police collect lots of data, and much of this information is spread across different police information systems. To determine which existing police datasets could provide information on DVA events, victims and perpetrators, the researcher had several meetings with police analysts and staff. From these meetings, four quantitative datasets were selected and extracted for analysis: recorded crime, offenders, incidents and DASH assessments. This section will outline each of these datasets and demonstrate why the data were deemed unsuitable for measuring patterns of DVA and police action.

3.2.1. Data extraction

To conduct the research, the researcher was allocated a force laptop (see Ethics). The force laptop provided access to some force information systems and data, though the data available for extraction was limited by the researcher's level of access. As the force analyst had a higher level of access, the analyst extracted the requested data. Three years (2015-2018) of DVA crime data were requested with information on victims, perpetrators, events and police action. Three years were selected as the optimal period to capture repetitions over rolling 12-month periods whilst maintaining a manageable amount of data (see Brimicombe, 2016). To extract the data, the analyst generated a list of all crime reference numbers (CRNs) with a 'domestic violence' flag attached. The CRN was used to extract all of the associated crime, offender, victim, modus operandi, officer report and address details. The variables were extracted using standard fields in the data sources. Standard fields are pre-coded points of data collection in police systems, sometimes appearing as drop-down menus from which pre-coded options are chosen, for instance the sex of the victim. Victim and perpetrator details were stored separately on force information systems, and therefore extracted as separate datasets. For perpetrators, information on *offenders* and *suspects* were stored separately. 'Suspects' refers to identified suspects that do not receive a disposal for the offence, 'offenders' refers to identified suspects that do. The use of this distinction in police data recording was not known by the researcher at the point of data request, and only data on *offenders* were extracted by the analyst for the study. The term offenders is therefore used hereafter to refer to the perpetrators extracted in the existing crime data. From the observations and meetings, DASH was also identified as a source of data with information for the substantive research questions. The analyst extracted all DASH assessments associated with the list of CRNs.

As discussed in the Literature Review, recorded crime cannot measure DVA repetition that is reported to the police as it only includes events that are crimed. Additional data on incidents were therefore requested from Command and Control, the unit responsible for allocating a police response when a report is made to the force. In incident reports, DVA cases are identified through the use of incident codes or flags. Incident codes include 'Domestic Incident' and 'Domestic Crime', flags include 'Domestic Abuse' and 'Domestic Incident'. In the meeting with Command and Control it was determined that the opening incident code is the most accurate means of identifying DVA incidents. Command and Control therefore extracted three years (2015-2018) of incident reports that had been opened with a domestic incident code.

The data were sent to the researcher via internal email that could be accessed through the police force laptop. All data were sent as Microsoft Excel spreadsheets.

3.2.2. Available datasets

The aim was to merge the existing datasets into one quantitative dataset with information on victims, perpetrators, events and police action. Each of the datasets is outlined here.

Recorded crime data

Recorded crime data refers to events that were reported to the police, subsequently recorded as a crime with a domestic violence flag attached. The data contain information on the event, including the date and time, the offence code, multiple categorical modus operandi variables, the crime outcome (e.g. whether the offender was charged, case closed, evidential difficulties), and information on the victim, including their name, home address, date of birth, sex, nationality and ethnicity.

The crime data contain all crimes that were recorded with a domestic violence flag between 2015-2018. This produced 33,948 crimes.

Offender data

The offender data refers to the offenders that are attached to the CRNs in the recorded crime data. The data contain information on the offender, including their name, home address, occupation, date of birth, sex, nationality, ethnicity and relationship to the victim.

The offender data were extracted by a police analyst using the CRNs. This produced 9,372 offenders.

DASH risk assessment

The DASH data refer to the DASH risk assessment that should be carried out for any reported event of DVA, regardless of whether the event results in a crime report (Richards, 2009). As stated in the Literature Review, DASH is a tool used by police forces in England and Wales to assess the risk of further violence when DVA comes to police attention. The assessment has 27 questions that should be asked of the victim relating to different forms of abuse including coercion, threats and intimidation, physical abuse, sexual abuse, children and pregnancy, and economic abuse. The DASH data available are the DASH assessments for each of the offences in the recorded crime data. The data contain binary yes/no answers to each of the 27 questions, the risk classification given to the offence, the date and time of the event, the victim's sex and date of birth.

DASH data were extracted by a police analyst using the CRNs, this produced 15,974 DASH assessments. DASH were not extracted for incidents.

Incident data

The incident data refer to the incident log opened by Command and Control when an event is reported to the police. An incident report should be opened for every event that is reported to the police, whether the event does or does not result in a crime report. The extracted data contain information on the recorded incident codes and address of the event.

An analyst in Command and Control extracted all incidents that had been opened with a 'domestic incident' or 'domestic crime' incident code between 2015-2018. This produced 65,265 incident logs.

3.2.3. Formatting and anonymization

Prior to the data being removed from police systems for analysis, the data were de-identified by the researcher using Microsoft Excel.

The crime data had identifiable information on the victims and offenders, including their full name, date of birth (DOB) and address. The incident data had no information on victims or offenders, though included the address of where the event took place. The DASH data had no identifiable information on victim or offender. All datasets had an event identifier, either an incident log reference number (ILRN) and/or a crime reference number (CRN). To measure DVA repetition requires that the data have units of measurement for the victim, offender and event, though the information that identified victims and offenders had to be removed from the data. To de-identify the data and retain the required units of measurement, unique ID numbers were assigned to each repeat victim and offender. To consider the address as a unit of measurement, each address across the datasets was given a unique ID number.

For victims and offenders, the force allocated a unique identifier to each individual, as part of force crime recording practice. The identifier combined the individual's surname and DOB. To de-identify the data whilst identifying repeat individuals, a new number was assigned to every matching police identifier in the data using syntax in Microsoft Excel. The original force identifier and name variables were then deleted.

To assign a number to each repeat address first required formatting. Addresses were recorded in multiple formats throughout the data. There were different spellings, abbreviations (e.g. Street or St.) and punctuation that prevented matching addresses from being identified. To ensure matching addresses were given the same ID number, the data were manually edited to correct differences in spelling and punctuation. All street names (e.g. road, place, court, avenue) were replaced with their abbreviation (e.g. RD, PL, CT, VE) to ensure all were consistent. All punctuation was removed. For addresses that were recorded as unknown, the variables were manually checked and edited to ensure that each 'unknown' was recorded in the same way. In the raw data, unknown fields were recorded in multiple formats e.g. through punctuation '-', '.', through 'XXXXX' or through the word 'UNKNOWN'. For addresses with partially unknown information, for instance where only the town name was given, the variables were checked to ensure unknown fields were recorded in the same format, and the given information was kept. Once formatted, the variables were concatenated into one address variable in each dataset. Where all address variables were completed, this produced a complete address. Where there was partially missing information, a full address could appear as a mixture of unknown and known information, such as 'XXXXXXTOWNNAME'. A unique ID number was then assigned to each matching full address in each dataset. Multiple events with partial information produce false repeats e.g. if multiple events all occur in the same town, and for those events only the town name was recorded, the single events appear as the same address. The original variables were then deleted.

The age of victim and offender in years was calculated by subtracting the date of the offence from the individual's DOB. The DOB variables were then deleted. All other identifiable information including any free-text fields were deleted.

Following formatting, the datasets were merged for analysis. To merge the datasets required that each had a common identifier. The original ILRN and/or CRN was therefore kept in the dataset as the common identifier. Each dataset was sent back to the analysts to ensure that the de-identification met force standards. The de-identified data were extracted from force information systems via external email.

3.2.4. Merging datasets

Each Excel dataset was read into SPSS v 26.0 as individual datasets. The four datasets were match-merged in SPSS using one common identifier. Each merge adds cases to the dataset. Starting with the crime dataset, the offenders dataset was merged using the CRN in each dataset. The DASH assessment dataset was then merged using the CRN. Finally, the incident data were merged using the ILRN in the crime and incident datasets. The final dataset contained all cases from each dataset and added variables to the cases that appeared in multiple datasets.

3.2.5. Descriptive analysis

Descriptive analyses were conducted on the individual and the merged datasets using descriptive commands in SPSS such as frequency tables and cross-tabulations. Descriptive analyses look at the prevalence of variables in each dataset, such as the offence types in the crime data, and the incident response grades in the incident data.

3.2.6. Structure of the original police datasets

Each dataset was originally collected for operational purposes and contained a different but overlapping sample of DVA events. Each had a different sample size and contained different units of measurement. Table 3.1 gives a summary of each dataset.

Table 3.1 Size of original police datasets and units of measurement

Dataset	Number of cases (2015-2018)	Available identifiers (Yes/No)			
		Victim	Offender	Address(es)	Event
Crime	33 948	Yes	No	Yes	Yes
Offenders (disposals)	9 372	No	Yes	Yes	Yes
DASH	15 974	No	No	No	Yes
Incident	65 265	No	No	Yes	Yes

The number of crimes flagged as DVA (33,948) was around half of the number of incidents (65,265). This is consistent with national figures that around half of DVA reported to the police results in a crime report (ONS, 2019a). Less than one third of crimes (9,372) resulted in a disposal against a known offender, and less than half of crimes (15,974) had an associated DASH. In all cases of crimed and non-crimed DVA, responding officers should complete a risk assessment (CoP, 2020b), though the figures in Table 3.1 suggest DASH was completed for only half of offences.

The datasets had different units of measurement. All datasets were structured by events, which means each dataset contained a sample of events, and multiple events could relate to the same victims and perpetrators. Each event had at least one event identifier: the incident log number and/or a CRN. The crime data had information on victims. The force identified victims using a unique identifier key allocated to each victim. The key was a combination of the person's surname and DOB. The crime data had the address of the event and the home address of the victim. In the offender data, the force identified offenders using a unique key identifier that combines the person's surname and DOB. The offender data had the offender's home address. The DASH data only had a CRN, and did not have any information on victims or perpetrators. The incident data contained no information on the victim or perpetrator, though had the address of the event.

From merging and descriptive analysis of the datasets, the data were deemed unsuitable for addressing the substantive questions. The key problem was that the structure of the datasets made them unable to accurately identify and measure DVA repetition. As repetition could not be estimated, patterns of DVA repetition could not be identified. Furthermore, there was a lack of information across the datasets on action taken by the police. This was both due to variables not being recorded consistently across datasets, and some variables not being recorded as standard fields and being lost in free-text.

3.2.7. Identified issues in the original police datasets that made the data unsuitable for measuring patterns of DVA

There were four key issues identified in the original existing police datasets that prevented their ability to measure repetition or police action: different units of measurement, inconsistent recording of personal details, applications of DVA identifiers, and free-text.

3.2.7.1. Units of measurement

To measure DVA repetition requires at least three units of measurement: victim, perpetrator and event (Walby et al, 2017). To merge the datasets requires that they have common identifiers that allow cases to be matched across each. Each dataset contained different units of measurement. Crime, offenders and DASH could be merged together using the CRN, adding information on offenders and DASH variables to the crime victims. To add information on incidents relating to the same victims or offenders/perpetrators would require that the incident data had units of measurement for the victim and perpetrator, this would enable the measurement of repetition. The incident data had no information on the victim or perpetrator. The incident and crime data both had event or address identifiers that could enable them to merge. However, the address in the incident data was the address of the offence, the address in the crime data was the victim's home address, and in the offender data was the offender's home address. These could be three different addresses, and therefore could not be able to match cases across datasets. Furthermore, addresses are not an appropriate unit of measurement for DVA repetition, as victims may continuously move addresses whilst trying to evade the perpetrator (Bowstead, 2015; 2017). The incident and crime data were therefore merged by the ILRN. This added additional information to the crimes, but any incidents relating to the victims and offenders could not be identified in the incident data, therefore not improving the measure of repetition.

3.2.7.2. Recording personal details

To match repetition in the data requires information that can identify individuals, such as name, address, and DOB. When all identifiable details are recorded, repeat individuals can be identified with greater accuracy (Brimicombe, 2016). Across the datasets, the police often did not record each identifier and there were lots of missing data. When personal identifiers were recorded, they were sometimes recorded in multiple formats that prevented repeat individuals from being matched.

The same name could be spelt in more than one way (e.g. Stephen, Steven) or shortened (e.g. Ste, Steve) meaning the same person may have multiple records using different variations of the same name and so repetition is missed. The same problem applied to addresses, which is the only piece of identifiable information provided in the incident data. An address could be recorded with a variety of spellings, punctuations and abbreviations and if an address was not recorded in the same format every time the repetition was missed. To prepare the data for analysis required manual checking and recoding of all name and address fields in the provided datasets to ensure all matching names and addresses were recorded in the same format, with the same spelling and punctuation throughout. This process is time-consuming though necessary for identifying repetition in police data (Farrell and Pease, 1993).

In the crime data, the force attached a unique identifier to victims and offenders. When the key was recorded consistently, it could be used to match repeats. This should reduce the need for all individual identifiers (i.e. name, address) to be consistently recorded for each individual. However, like with other personal details, the identifier key was not recorded for all crimes in the data therefore repetition was likely missed. Furthermore, the key was derived from a combination of the individual's name and DOB. This could suggest that the individual requires a change of key if the individual changes personal details e.g. removing marital surname. A nominal identifier attached to individuals overrides some of the issues causes by inaccurate recording of personal details, but the nominal should be resistant to changes in personal details for it to be effective. Moreover, the identifier key was only available in the crime data and there was no key provided for incidents, thus the majority of repetition is lost.

3.2.7.3. DVA identifiers

The second issue identified in the police data recording practices that prevents the identification of repetition is the methods of identifying DVA in police data. The analysis found issues both in the interpretation of events classified as DVA, and in the use of multiple identifiers. The Home Office requires that police forces manually 'flag' notifiable offences that meet the definition of DVA (violence or abuse between intimate partners or family members) (Home Office, 2020a). Descriptive analysis of the crime data found several offences flagged as DVA that did not fit the definition.

This included crimes where the victim was recorded as business/state, thus the victim and perpetrator could not fit the DVA definition, and offence types where the stated victim does not match the DVA definition. Table 3.2 provides a list of all of the offence types in the dataset that were recorded with a DVA flag, ordered by the most commonly appearing offences. An example was a shoplifting offence, in which two offenders used a child to conceal goods they had stolen from a store. The victim recorded in the crime was 'business' i.e. the store, though the crime was flagged as DVA. There is no information in the free-text field that indicates why this crime was flagged as DVA. This also included crimes where an individual was recorded as the victim that was not an intimate partner nor family relation of the perpetrator. An example was seven offences of assault against a

Police Constable (PC), where a PC had been assaulted whilst attending a DVA event. The PC was recorded as the victim, though was not an intimate partner or family member of the perpetrator, therefore the recorded crime did not fit the definition of DVA, though was flagged as a DVA crime. As shown in Table 3.2, there were also offences against children, for instance 23 (0.1% of offences) crimes of rape of a female child under the age of 13 years. The Home Office definition of DVA applies only to persons aged 16 and over, thus these crimes do not fit the criteria for DVA.

Table 3.2 Percentage of each crime type in original police recorded crime data

Crime	Frequency	Percentage (%)
Assault With Injury	10 807	31.8
Assault without Injury	10 042	29.6
Harassment	4 985	14.7
Criminal Damage Dwellings	1 747	5.1
Criminal Damage Other	1 026	3
Criminal Damage Vehicles	550	1.6
Rape of Female Aged 16+	536	1.6
Malicious Communications	484	1.4
Wounding	471	1.4
Other Public Order Offences	458	1.3
Threats to Murder	455	1.3
Theft in Dwelling not from Machine/Meter	355	1
Other Theft/Unauthorised Taking	269	0.8
Public Fear Alarm/Distress	248	0.7
Treat/Possession with Intent to Commit Criminal Damage	248	0.7
Sexual Assault on a Female aged 13+	126	0.4
Burglary Dwelling	114	0.3
Burglary Residential	109	0.3

Stalking	96	0.3
Stealing Motor Vehicles/Unauthorised Taking Motor Vehicle	95	0.3
Theft from the Person	70	0.2
Perverting the Course of Justice	63	0.2
Kidnapping	52	0.2
Criminal Damage Other Buildings	36	0.1
Robbery of Personal Property	34	0.1
Cruelty to Children/Young Persons	29	0.1
Rape of Female Child Under 16	26	0.1
Possession of Article with Blade/Point	25	0.1
Sexual Assault on a Female Child under 13	25	0.1
Rape of Female Child Under 13	23	0.1
Theft from Vehicle	21	0.1
Blackmail	21	0.1
Arson not endangering life	21	0.1
Arson endangering life	17	0.1

Attempted Murder	16	<0
Shoplifting	15	<0
Burglary in a Building Other Than a Dwelling	14	<0
Other Miscellaneous Sexual Offences	11	<0
Other Notifiable Offences	11	<0
Possession of Controlled Drugs (Cannabis)	11	<0
Murder	:	<0
Obscene Publications Offences	:	<0
Aggravated Burglary in a Dwelling	:	<0
Possession of Other Weapons	:	<0
Possession of Controlled Drugs excluding Cannabis	:	<0
Sexual Assault on a Male aged 13+	:	<0
Rape of Male Child Under 13	:	<0
Aggravated Vehicle Taking	:	<0
Sexual Activity involving a Child under 16	:	<0
Theft of Pedal Cycle	:	<0

Dangerous Driving	:	<0
Assault without Injury on a Constable	:	<0
Exposure/Voyeurism	:	<0
Racially/Religiously Aggravated Harassment	:	<0
Racially/Religiously Aggravated Public Fear Alarm or Distress	:	<0
Possession of Firearm with Intent	:	<0
Attempted Burglary in a Dwelling	:	<0
Causing Sexual Activity without Consent	:	<0
Incest/Familial Sexual Offences	:	<0
Racially Aggravated Assault without Injury	:	<0
Racially or Religiously Aggravated Assault with Injury	:	<0
Trafficking in Controlled Drugs	:	<0
Child Abduction	:	<0
Endangering Life	:	<0
Rape of Male Aged 16+	:	<0
Aggravated Burglary - Residential	:	<0

Attempted Burglary - Residential	:	<0
Attempted Burglary in a Building Other than a Dwelling	:	<0
Burglary – Business/community	:	<0
Modern Slavery	:	<0
Offender Management Act	:	<0
Possession of Firearms Offences	:	<0
Theft – Making Off without Payment	:	<0
Theft from Automatic Machine/Meter	:	<0
Theft by Employee	:	<0
Theft of Mail	:	<0
Vehicle/Driver Document Fraud – Police Record	:	<0
Exploitation of Prostitution	:	<0
Going Equipped for Stealing	:	<0
Interfering with a Motor Vehicle	:	<0
Child Destruction	:	<0
Sexual Assault on a Male Child under 13	:	<0
Sexual Activity involving a Child Under 13	:	<0

Frequency counts below 10 are not shown

Table 3.3 displays the sex distribution of the victims recorded in these offences, showing that almost a quarter of the crimes recorded and flagged as DVA in the dataset were recorded as against the state (24%), with a further 39 (0.1%) recorded against a business, and 32 (0.1%) recorded with an unknown sex. The use of the DVA flag when recording some of these offence types may partially explain the lack of DASH assessments available in the crime data that were provided by the force. If the nature of the event did not fit the definition of DVA, then the event may not have required a DASH. These events are more likely to be singular rather than repetitive, and when included in the data could contribute to an underestimate of repetition in the DVA that comes to police attention. DASH may also be missing due to refusals or non-completion. Furthermore, the police response to these events may not reflect how the police would respond to an offence of DVA that does fit the definition, therefore would affect an accurate evaluation of how police actions relate to DVA repetition.

Table 3.3 Sex of victims in original police recorded crime data

Sex of victim	Frequency	Percentage (%)
Female	19 743	58.2%
Male	5 979	17.6%
Business	39	0.1%
State	8 155	24%
Unknown	32	0.1%
Total	33 948	100

In addition to different interpretations of DVA flags, there are multiple methods for the police to identify DVA when recording, which affects the sample of DVA events that are extracted. DVA crimes are identified with a DVA 'flag', and the Home Office (2020a) require that the police attach an additional 'repeat DA' flag if a DVA crime fits their definition of repeat. One crime can thus have two DVA flags. In the force data, incidents had a separate 'domestic abuse' (DA) flag and 'domestic incident' flag. Incidents could also be opened with a 'Domestic incident' or 'Domestic crime' incident code, and/or closed with one of these codes. Opening and closing codes may differ. Crimes and incidents may be recorded with varying combinations of flags and codes. Codes or flags were used to identify and extract the DVA data, the incident data provided by the force were extracted using the opening incident code. Therefore, if an incident had been opened with a non-domestic incident code, though later flagged as DA, the incident would be excluded from the extracted data. For every DVA event, there should also be an associated DASH and DA referral. DVA events could be extracted from incident data, crime data, DASH data, and referral data. A subset of DVA events may be included in every data source, though some will only be recorded in one or some, depending on the code or flag used, and whether a DASH and referral were submitted. Some DVA events may also be missing completely from these sources if they were never recognised by police as DVA. If one source is used to extract DVA events, or if one code or flag is used to identify events, only a subset of DVA events will be extracted.

During the study, Lancashire Constabulary had a new information system implemented across the force that changes the way events are recorded by the force. In the new information system, the DVA flag prompts the recording officer to complete additional tasks required for DVA events, such as uploading the DASH. The repeat DA flag does not prompt the additional tasks. As the repeat DA flag requires less administrative tasks, police analysts within the force have stated that recording officers sometimes use the repeat DA flag instead of the DVA flag. This anecdote further suggests that adding methods of identifying DVA in police data furthers inconsistencies in police recording of DVA.

3.2.7.4. Additional information in the free-text

The final issue with the existing police datasets is that they do not capture some of the additional information found in the free-text fields that may improve the measure of DVA repetition and provide further information that may contribute towards an analysis of police action. All variables in the crime dataset were numeric or categorical, other than one free-text field. The free-text field provided a short written summary of the case by recording officers. The amount of information and the type of information written in the free-text field varied considerably between cases. For some cases, the free-text field was a one-line summary of the event, for other cases the free-text field provided more information on any action taken by the police, and any additional information on the victim and perpetrator that was relevant to the event and the response. The free-text field demonstrated the type of information that is collected by police that is not captured by the standard fields.

One example is where the free-text indicates there may have been further offences that did not appear in the crime data. In one offence recorded in the crime data, the free-text field states:

> *'Offender attacks victim in park on the way home. Both parties live together. Case follows an incident from the night before where offender assaulted victim.'*

The free-text may indicate that there was another offence of assault between the dyad that was reported the previous evening though was not recorded as a crime, or was recorded and not flagged as DVA. The free-text could indicate that both offences were reported at the same time and thus one offence was recorded per counting rules (Home Office, 2020a). There may be further information not available in the short free-text that explains why the previous offence did not appear in the crime data.

The free-text also provides further information on the DVA event than the standard fields. The additional information could contribute to the understanding of DVA events that comes to police attention and may provide further understanding of police decisions on risk and interventions. One example is where multiple offences take place in the same event, though only one is recorded as a crime (following the Home Office Crime Recording rules), thus information on the other offences is lost when looking only at standard fields.

An example of one case was:

> *'During verbal argument offender grabs victim and drags her up and down the hallway causing reddening to underarms and pain to head. Police attend, victim initially does not disclose but states cohabiting ex-partner makes vague threats to burn house down.'*

This offence was recorded as assault with injury, though also involved threats to commit arson that were not captured in the standard fields. Collecting information on the multiple offences that occurred within one recorded event could provide a better understanding of the type of events that come to police attention and be important for determining risk and intervention. Such information should therefore be recorded as standard fields.

3.2.8. Summary of original police datasets

To measure patterns of DVA repetition and police action requires information on the victim, perpetrator, event and any action taken by the police. Meetings with staff and analysts within the force identified several datasets where information on each of these areas was collected. These original datasets were recorded crime, offenders, DASH and incidents. These data sources had standard fields from which data could be extracted from force information systems into quantitative datasets for statistical analysis. The four datasets were de-identified, formatted and merged by the researcher to produce one dataset that combined all events and all available variables. However, the process of formatting the data and exploratory descriptive analysis found the data unsuitable for measuring DVA repetition and police action. The key issues with these original datasets were the different units of measurement, inconsistent recording of personal details, incorrect use of DVA flags and multiple methods of flagging DVA, and the embedding of useful information in free-text narratives.

3.3. Finding alternative sources of police data

Alongside the extraction and exploratory analysis of the existing datasets, the first phases of the research design involved a series of overt observations of the police response, as well as informal meetings with officers and staff across various units of the force. The initial purpose of the observations was to map the police response, to gain deeper understanding of the stages, processes and personnel involved that should be considered when looking at DVA repetition in police data and assessing the impact of any actions taken by police, and to identify the different points of data collection. Observations of the police provide first-hand insight into the cultural nuances of the police and provide opportunity to contextualise the rest of the research and refine measurement tools (Walklate (in Westmarland, 2011); Reiner, 2000). The police response was followed from the point of a report being made to the police investigation and involvement of other agencies. Six components of the response were observed: Command and Control, frontline response, Criminal Investigation Department (CID), Public Protection Unit (PPU), Multi-Agency Safeguarding Hub (MASH) and Multi-Agency Risk Assessment Conferences (MARACs). The observations were an initial scoping exercise to contextualise the research. This section describes each the main contacts with the force and presents maps of the response process derived from these observations.

3.4. Access to the field

The project is a CASE studentship sponsored by Lancashire Constabulary. As part of the contractual agreement between the researcher, the university and the police, a non-academic partner supervisor was allocated to the project (see Ethics). The partner supervisor facilitated contact between the researcher and each observation site or force unit to grant access to space and personnel for the study. The contact for each observation site was made aware and agreed to the observation. Each individual observed one-on-one was asked and gave permission for the observation to take place, and was made aware that information taken from the observation would contribute towards the research project.

3.4.1. Collecting data from observations of the police

Information was collected from each observation site using field-notes made free-hand in a physical research journal. Each observation site was aware of notes being taken. Notes were made only when deemed appropriate and the least obtrusive observation (see Reiner, 2000; Gravelle and Rogers, 2014). All field-notes were written up comprehensively and digitally following the observation. All sensitive information taken from the observations remained confidential and data were managed in line with the contractual agreement between the researcher, the university and the police force, and with the university faculty Ethics Committee.

3.4.2. Observation sites

Six areas of the police response were observed. The observation sites are presented here in typical order of appearance in the police response, rather than order of the observations.

In addition to the observations listed, meetings were held with officers and staff in the force and partner agencies to discuss the available data. Meetings included Command and Control, force analysts, Domestic Violence Disclosure Scheme (DVDS) review team, and MASH team leaders. Meetings were face-to-face and/or over the telephone. The observations and meetings were treated as a scoping exercise to contextualise the research, examine the process and data practices. Information from the observations was later mapped to visually show the complexity of the police response and highlight areas of data collection. As the original datasets extracted by the force were deemed unsuitable for the project, the findings of observations identified alternative data sources that could contribute towards the analysis of DVA repetition and police action.

Command and Control, May 2018

Shadowing of two police call-handlers at Lancashire Constabulary headquarters, partially covering a Thursday afternoon and evening shifts

Command and Control are responsible for allocating the police response when events are reported to the police (CoP, 2018a). When a call comes through to Force Control Room (FCR), call handlers within Command and Control grade the incident to determine the level and speed of initial police response (ACPO, 2005). To observe the collection and sharing of data, call handlers were shadowed whilst taking live 101 and 999 calls. Access to Command and Control was facilitated by the partner supervisor via email with the researcher and a Police Inspector (PI) based within the FCR. The observation took place on a Thursday afternoon - evening shift, as the PI indicated that the FCR receive the most DVA calls on Thursday, Friday and Saturday evenings. To listen to the calls as they were being taken, additional headphones were plugged into the call handler's telephone to enable the researcher to hear the interaction between informants and the call handler. Two call handlers were separately shadowed. Between listening to calls, the call handlers were spoken to informally about their role, the process of responding to calls and allocating a police response, the type of information collected and the systems used. Field-notes were made whilst sat with the call handlers.

Frontline response, June 2018

Ride-along with two PCs in one city centre, partially covering a Friday evening shift.

Depending on the grading of the reported incident, FCR may deploy frontline officers to the incident. To gain insight into the components of the frontline response, two PCs were separately observed on ride-alongs. The partner supervisor and a Police Sergeant (PS) in a city centre police station in the force area facilitated the observation. As most DVA reports are made in the evenings and weekends, a Friday evening shift was chosen. The observation started with a team briefing with all officers at the station starting the evening shift led by a PS. The researcher was allocated to a PC to accompany them in a marked car to patrol the city centre, respond to any incidents and pick up deployments from FCR. Two PCs were accompanied separately throughout the same shift. During the ride-alongs, two DVA calls were attended. One call was a planned appointment with a victim following a suspected breach of a non-molestation order. For this call, the researcher shadowed the officer with verbal consent given by the victim. The second call was an emergency response picked up by the officer whilst on patrol. For this call the researcher remained in the police vehicle due to the greater risk posed by the live event taking place and both victim and perpetrator being present. In addition to the DVA calls, a non-domestic violent event was attended. The perpetrator had left the scene and the researcher was able to attend the local accident and emergency department with the PC and the victim. Between ride-alongs, the researcher met with the Officer in Charge (OIC) to discuss challenges facing the police with regards to demand and resources, specifically in relation to vulnerable persons including cases of DVA. Field-notes were made retrospectively in the police station between ride-alongs.

Criminal Investigation Department (CID), June 2018

Observation of a Risk and Threat meeting in one city centre police station on a Saturday morning, following the ride-along on the previous Friday evening.

CID is a specialist branch in a police force committed to investigating and developing intelligence on reported events. To follow the response from frontline officers to CID, the researcher observed CID on the Saturday morning in the city centre police station following the ride-along on the previous evening. The observation was facilitated with the same PS as the ride-along. The main purpose of the observation was to observe a risk and threat meeting. The risk and threat meeting is a virtual meeting between CID detectives in the different force areas to discuss the current high-risk cases across the force. Between arriving at the police station and the start of the meeting, the researcher spoke with detectives in CID about the process of investigating DVA cases and collecting and sharing information as part of this process. Field-notes were made during the meeting.

Public Protection Unit (PPU), January 2018

Shadowing of two PPU researchers at Lancashire Constabulary headquarters.

The Public Protection Unit (PPU) is a specialist police department that protects vulnerable persons and manages the risk posed by dangerous offenders. To gain a better understanding of PPU and the use of data in facilitating safeguarding, a Researcher in PPU was shadowed. The observation was arranged with a Detective Chief Inspector (DCI) in PPU. During the observation the Researcher demonstrated extracting data from force information systems. Field-notes were made throughout.

MASH, April 2018

Shadowing of a MASH referral assistant at one Lancashire Constabulary MASH site.

MASH is a hub in which local authority agencies, police, health and probation co-locate to share information and coordinate safeguarding decisions. At the time of the observation, all DVA events reported to the force were referred to MASH for safeguarding. To gain insight into the use of data within MASH, the researcher observed practice within a MASH during one weekday. The observation involved shadowing a Referral Assistant (RA), and speaking to IDVAs within the MASH. The observation was facilitated by the partner supervisor. There are three MASH sites within the force area. This site was chosen due to ease of access, as the partner supervisor was attending the MASH site and invited the researcher to attend in the same trip, though the supervisor was not present when the researcher shadowed the RA. The RA was shadowed whilst they reviewed domestic abuse (DA) referrals and populated them with information. Informal conversations were had with the RA and IDVAs within the MASH about their role, and the type of information gathered and shared. Field-notes were made throughout the observation.

MARAC, June 2018

Observations of two MARACs in two city centres within the police force area.

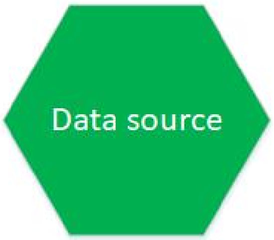
MARACs are multi-agency meetings where voluntary and statutory agencies, including the police, come together to share information on high-risk DVA cases. To understand the process of data collecting and sharing between agencies, two MARACs under two local authorities were observed. The observation was facilitated by the partner supervisor and the MARAC coordinator. Both observations lasted around 10am-4:30pm. During both observations the researcher was introduced as a researcher to the meeting and observed without participation. Field-notes were made throughout the observation.

3.4.3. Mapping observation sites and police data sources

Observations provided information on the stages and personnel involved in the police response to DVA, the processes of data recording and the available data sources. Visual maps were produced of some of response components, and one map summarises the full response. The maps highlight the actions, individuals/units/agencies and points of data collection. The maps are summaries and do not include all of the possible processes and personnel. All maps were produced in Microsoft Visio. This section describes each of the components and presents each of the associated maps. The subsequent section will outline the data sources that were identified in the observations and meetings across Lancashire Constabulary.

For each map, the key is as follows:

Table 3.4 Graphics key for response maps

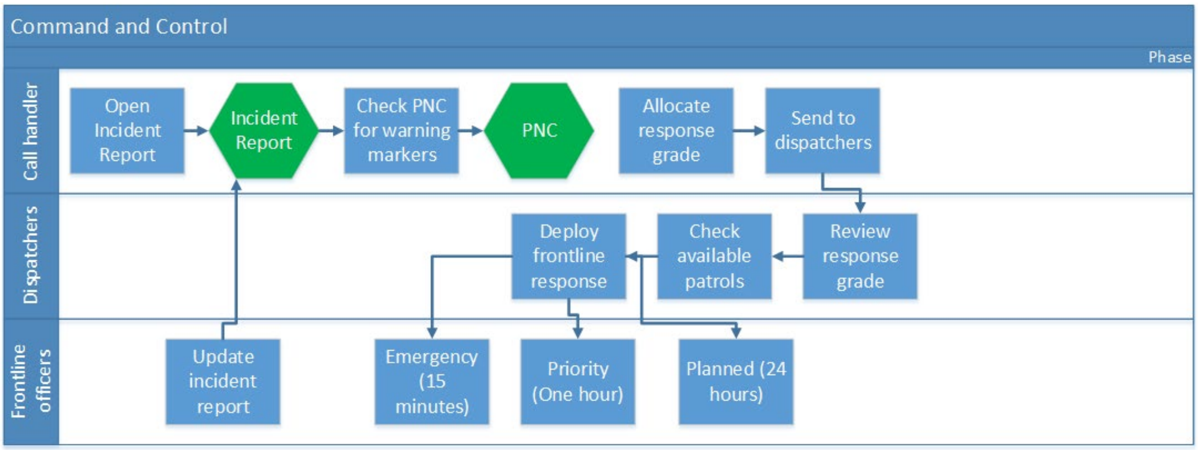
	Refers to an individual or unit within the police response that is involved in data collection and/or sharing e.g. a frontline response officer, a multi-agency safeguarding hub (MASH)
	Refers to an action or activity taken by an individual or agency in the response to DVA, particular focus is on actions that involve information collecting or sharing e.g. risk assessment, submitting a Crime Report
	Refers to a point in which raw police data are collected. A collection of data in any format, or a point from where data can be extracted e.g. an Incident Report, the Police National Computer (PNC)

3.4.3.1. Command and Control

Command and Control are responsible for allocating the police response to a reported incident, including deploying frontline officers (CoP, 2018a). As a 101 (non-emergency) or 999 (emergency) call comes into Command and Control, it is picked up by one of the police call-handlers. On answering a call, the call-handler opens the incident report and attaches an opening incident code. There are a multitude of incident codes to select. Some codes parallel offence types, such as assault, harassment and criminal damage. There are also two incident codes for domestic-related events, 'Domestic Incident' or 'Domestic Crime', depending on whether the reported event crosses the criminal threshold. Other incident codes include 'concern for safety', 'suspicious circumstances', 'personal', and 'civil dispute'. The circumstances of an event may fall under multiple incident codes, though only one is selected as the opening code. The incident report is opened on an incident system, within one of the force's main information systems. The call-handler then speaks to the informant to gather as much information as possible on the circumstances of the event and to coordinate the appropriate response. To build the incident report, the call handler may seek additional information from PNC. PNC can be used in this stage to identify any warning markers on the address of the event. The call handler may also seek information from other teams within

Command and Control, such as ANPR (Automatic number plate recognition) cameras. ANPR is used to identify vehicles of interest using the number plate (CoP, 2020a). ANPR can gather information on the vehicle using vehicle registration marks (VRM) such as the location in which the vehicle was most recently picked up by an ANPR camera, providing opportunity to disrupt and prevent crime. The call handler has an additional system to check what police response units are available to deal with the incident. The information provided by the informant and the actions taken by the call-handler are typed free-text by the call-handler directly into the incident report.

Table 3.5 Command and Control response map



From the information gathered, the call-handler allocates a response grade to the event, determining the level and speed of the police response (ACPO, 2005). There are five response grades used by the force: emergency, priority, planned, telephone resolution, and police report only. Figure 3.5 shows the three response grades that involve attendance by frontline officers.

'1: Emergency response: An incident where there is likely to be a risk of danger to life; use/ immediate threat of use of violence; serious injury to a person; serious damage to property. Attendance usually within 15 minutes.

2: Priority response: A degree of importance or urgency associated with the initial police action but an emergency response is not required. Attendance usually within 1 hour.

3: Planned response: Response time is not critical in apprehending offenders so response given by a member of the Neighbourhood Police Teams, an appointment at a fixed surgery or an appointment by a scheduled car. Attendance usually within 48 hours, or at an agreed time.

4: Telephone resolution: Resolution sorted at first contact. Does not require any further intervention outside the Communications Centre other than the passing of information or the recording of minor crimes.

5: Police report only: Where public assistance is not required, but an incident has occurred and a report needs to be written.' (Boulton et al, 2017: 75).

If the grading requires a frontline response, the report is given to the Dispatchers team to review the response grade and deploy frontline officers. If frontline officers are deployed, the incident report is then edited and updated by the responding officers. Responding officers may state whether they have been able to attend the incident and add any action taken whilst at the incident, including whether the suspect was arrested, whether the parties were separated and whether the victim engaged with the police response. When closing the incident report, the incident is given a closing incident code and any flags are added. The closing code may differ to the opening code.

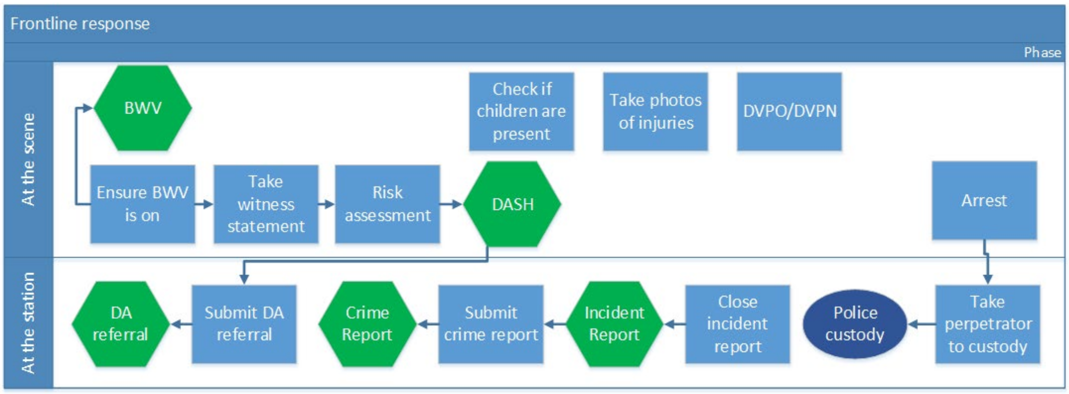
3.4.3.2. Frontline response

Frontline officers have two key roles when responding to an incident of DVA: to identify the signs of abuse and safeguard the victim from further violence, and to identify any criminal offences and deal with the offender (CoP, 2016). The frontline response is complex and may involve multiple actions, interventions, persons and agencies, and the exact response will vary from case to case. The map in Figure 3.6 presents a summary of some of the components involved.

When attending a DVA event, it is required that at least two police officers attend, and officers must wear Body Worn Video (BWV) cameras. At the event, frontline officers update the incident report with the circumstances of the event on arrival, and any action taken. The officers have a number of actions that they may take, including arrest of the perpetrator, separation of the victim and the perpetrator, and advice. The officers take a statement of events from the victim and should complete a DASH interview with the victim. The DASH is used to determine the risk of further violence and to assign a risk classification of standard, medium, or high-risk. In the early stages of the response, the officers should consider whether to administer a DVPN (domestic violence protection notice) or DVPO (domestic violence protection order). DVPNs and DVPOs provide short-term protection for the victim where there has not been an arrest, or where there has been an arrest of the perpetrator but the investigation is in progress (CoP, 2015d). The notices and orders are put in place to protect victims in the immediate aftermath by preventing the perpetrator from returning to a residence and/or having contact with the victim for a set period following the event (Home Office, 2020c).

Following attendance, officers return to the station to record details of the event and the response. The officers complete the incident report, and if the event crosses the criminal threshold, they also submit a crime report. The incident report is stored on an incident information system, and the crime report is stored on a crime information system. Both systems are linked, and are within one of the force’s main information systems. The crime report includes the Home Office crime classification, a short free-text description of the offence, a time-stamped log of actions taken and any relevant flags, such as DVA. If further investigation is required beyond the investigative actions taken by frontline officers, the Criminal Investigation Department (CID) will gather intelligence and pursue the case.

Table 3.6 Frontline response map



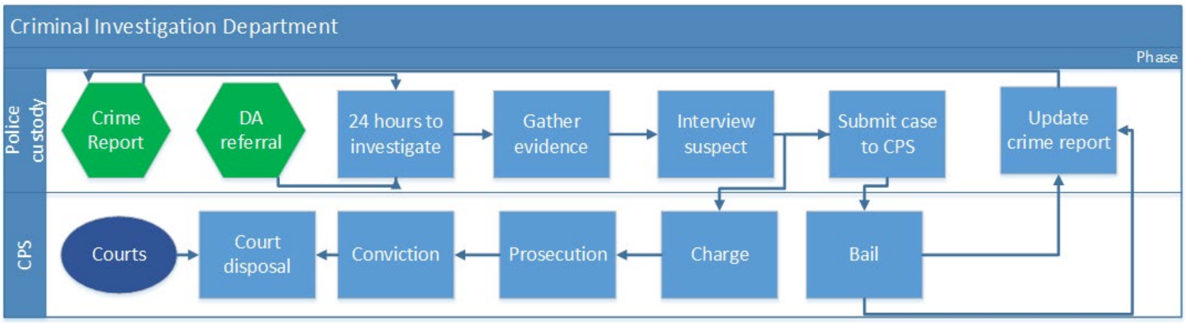
In addition to an incident report and crime report, for any crimed or non-crimed event of DVA, officers are required to notify the MASH. This is a practice across police forces in England and Wales, forces are required to notify safeguarding agencies of cases of vulnerable persons, including DVA (Ford et al, 2019). At the time of the study, officers were required to submit a domestic abuse (DA) referral to MASH to notify of a DVA event. The purpose of the referral was for the police to record and share as much information as possible on the circumstances of the event, the actions taken and any other relevant information with other agencies and organisations e.g. probation, IDVAs, health, to safeguard the victim from further violence. Responses to the DASH and the risk classification given were attached to the referral form. The referral was then sent to the local MASH to be reviewed and shared with relevant agencies to facilitate safeguarding.

3.4.3.3. CID

CID is a specialist branch in a police force committed to investigating and developing intelligence on reported events. For cases of DVA, CID pick up the crime report and incident report, and the DA referral. Additional data may be taken from frontline officers’ BWV footage for evidence. If the suspect is in custody, CID will communicate with the custody suite. From the point of the suspect being booked into the custody suite, CID have 24 hours to investigate the event and make a decision on whether to release or charge the suspect. Once CID have gathered enough intelligence to build a case, the case is submitted to the CPS for a charging decision. If there is not enough evidence to charge the suspect within the 24 hours, the suspect may be released without charge, with or without bail. In DVA cases, the bail conditions imposed on the suspect may be to not make any contact with the victim whilst on bail. The outcome of the crime is recorded on the crime report by the investigating officers.

For high-risk DVA cases, CID officers and detectives may share details of the case with other force areas in force risk and threat meetings, particularly if the suspect is still outstanding. CID update the crime report whilst investigating the case, though do not make any edits to the incident report or the DA referral. The CID observation demonstrates the collation of multiple data sources to build the case, and highlights the importance of data collection for providing sufficient evidence to pursue a case. CID take data that have been collected in earlier stages of the police response and gather further data through investigative activities such as suspect interviews. The quality of data collated by CID is crucial for submitting a case to CPS.

Table 3.7 Criminal Investigation Department response map



3.4.3.4. PPU

In UK police forces, incidents that involve vulnerable persons, including DVA, are managed by Public Protection Units (PPU) (Ford et al, 2019). PPU manage cases including DVA, vulnerable adults, vulnerable children, honour based violence, trafficking and missing persons (Ford et al 2019). A researcher was shadowed whilst they were producing a report on the most recent DVA figures for a force ‘Domestic Abuse Review’. The focus of the observation was on the forms of data available in PPU rather than the process of investigation and risk management.

The researcher gave an overview of the figures used to produce the force’s report on DVA and demonstrated how to collect these figures. The figures on DVA used by researchers were collated from multiple sources. Each division within the force was contacted by PPU with a list of questions on their DVA practice. This information would then be compiled to produce a report on force practice in DVA cases. Data were also gathered from one of the force’s main information systems. The system stores information on most areas of police activity, including incidents, crimes, victims and offenders. PPU researchers extract quantitative information from the standard fields in the incident report and crime report when producing research figures on DVA. Data on incidents and crimes can be downloaded as a csv file directly from the system. Data can be downloaded with specific filters and a selected time-period, though there is a limit on the number of cases that can be exported, which restricts the scope of the data selection. The researcher referred to the available information as 'surface data', and more detailed and larger quantities of data would have to be requested from force analysts with higher data access. Data for the DVA report were also gathered from MARAC. In the PPU research report, data from MARAC were used to discuss the most high-risk cases that had been recorded by the force, and were used as a measure of repetition. The number of repeat cases that were heard at MARAC defined the level of repetition in DVA cases. A repeat was defined within MARAC as a second MARAC referral relating to the same dyad within 12 months of the original or previous referral.

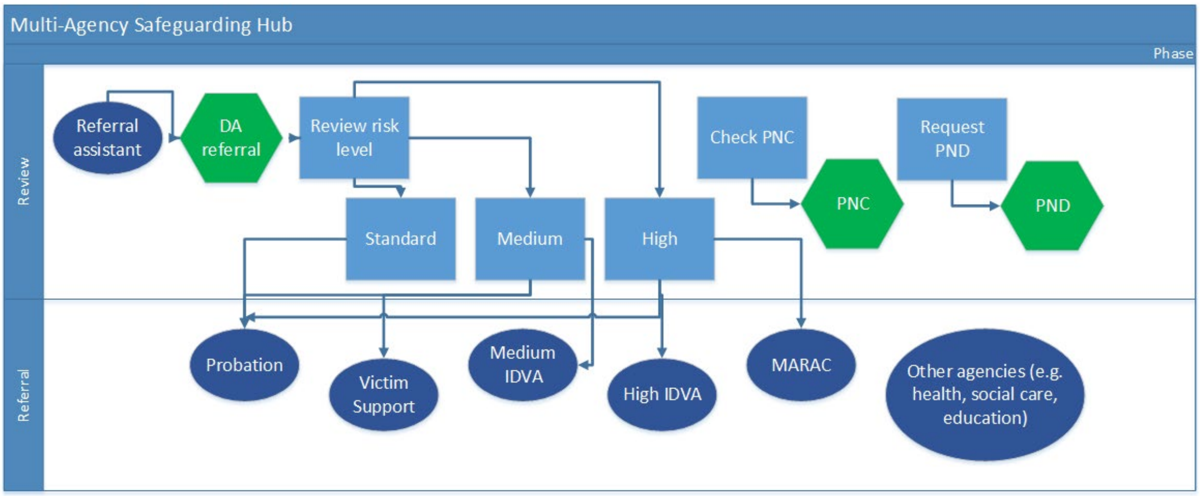
The observation of PPU focused on the use, definition and extraction of DVA from police information systems. The observation highlighted the non-standardisation of DVA information collection and definition between divisions and units within the force and showed the complexity of the available information. PPU demonstrated that there are multiple data sources collected in relation to DVA, including incident reports, crime reports, DA referrals, and MARAC reports. Some data were available for extraction by the researchers directly from force information systems. For larger datasets with a greater number of fields and cases, data had to be requested from force analysts.

3.4.3.5. MASH

MASH is a multi-agency information sharing model used by many force areas across England and Wales (Home Office, 2014a). Since the observation in April 2018, there has been a new IT system implemented across the force and a review of the MASH process. Both have had an impact on MASH processes. The data extracted for this study were not affected by the changes in system or process.

Once officers have submitted a DA referral, it is reviewed and processed by MASH. Research Assistants within the MASH review the risk classification, populate the referral with further information and share the case with relevant agencies and organisations. The risk classification allocated to the referral determines the level of information that is added and the number of agencies and/or organisations that the referral is shared with. The risk level is first allocated by frontline officers, though may be increased or decreased by MASH. For standard-risk referrals, minimal information is added and the referral is not usually shared with other agencies, other than probation. There is often no IDVA for standard-risk cases. For medium-risk cases, the referral may be shared with probation, a medium-risk IDVA, Victim Support, and any other relevant agencies. For medium-risk cases, the number of previous referrals relating to the dyad is added to the referral. Depending on the circumstances of medium-risk cases, MASH may seek further information on the victim and perpetrator from PNC. PNC contains conviction history on the victim and perpetrator. Conviction history includes offences recorded by any police force in England and Wales. Some medium-risk cases may be referred to MARAC if they meet certain criteria. Certain criteria include if there have been three crimed incidents for the dyad within the last 12 months, if there are 14 or more ‘yes’ ticks to the DASH questions, the seriousness of the presenting event, and the professional judgement of the OIC. An event may be re-referred to MARAC if violent and/or relates to stalking/ harassment within 12-months of previously being heard. Cases referred to MARAC are heard within four weeks. The amount of information added to the referral is guided by the risk classification.

Table 3.8 MASH response map



Of all cases reviewed by MASH, high-risk cases are prioritised. For high-risk cases, MASH build a police chronology for the perpetrator and victim, using information from PNC and PND. Information from PND includes all contact that the person has had with the police, and any intelligence that the police have in relation to the person. Information from PND includes all UK police forces. MASH cannot extract information from PND itself, but have to request information from PND. Requests to PND must specify a time-period, for instance a PND request may ask for all police contact for a person in the last two years. High-risk cases are shared with probation, High-risk IDVAs, Victim Support, any other relevant agencies, and MARAC. A High-risk IDVA will make contact with the victim within 48 hours of the event coming to MASH’s attention. The IDVA will make three phone calls to the victim before closing the case, as well as facilitating safeguarding measures. All high-risk cases are referred to MARAC.

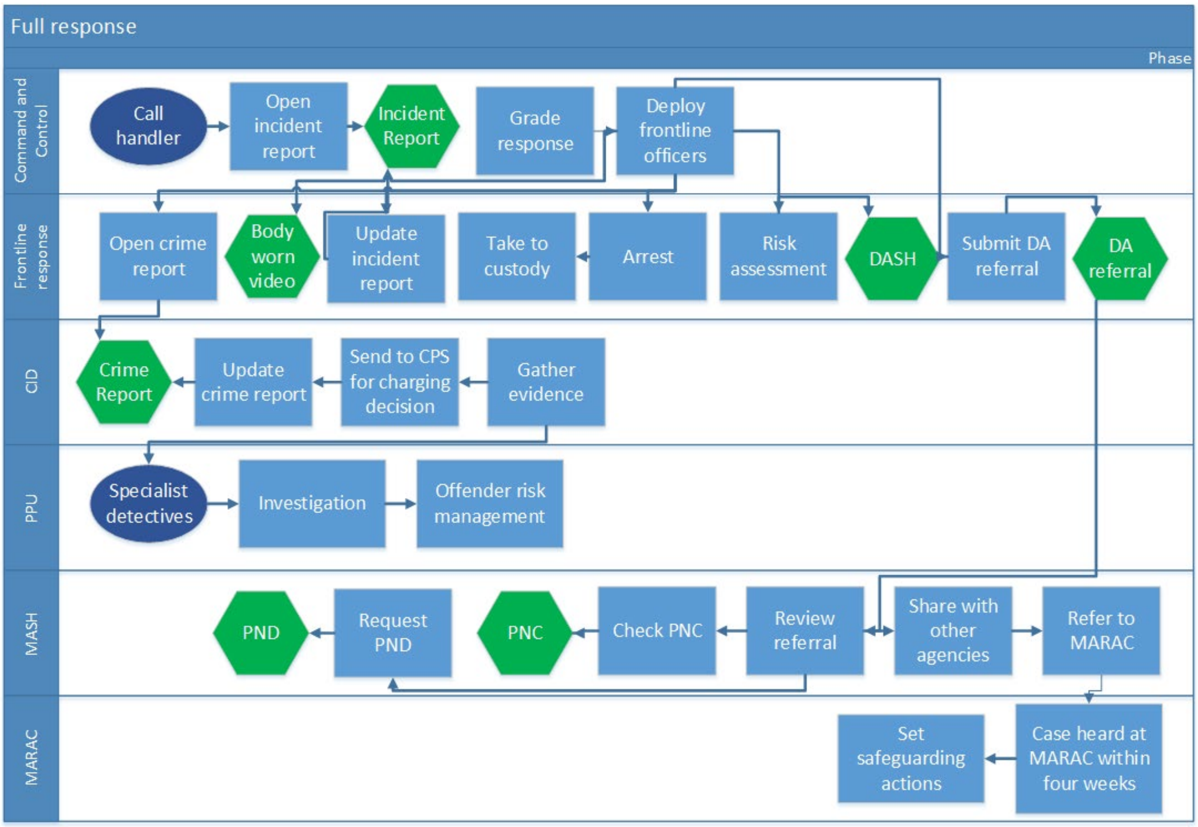
3.4.3.6. MARACs

MARACs are multi-agency meetings that bring together statutory and voluntary agencies to share information on high-risk cases of DVA to jointly coordinate a safeguarding plan for the victim to prevent further violence (Steel et al, 2011). In each MARAC meeting, all DVA cases that were referred since the previous MARAC meeting were discussed. The MARAC report for each DVA case was read aloud to the meeting participants by the MARAC coordinator. The MARAC report detailed what happened in the presenting event and gave information on the perpetrator and victim, and a brief history of the DVA between the dyad. The representative(s) from each agency then shared any information they had on the victim, perpetrator, and any children of the dyad, and recorded any information shared with them that may affect their safeguarding and/or interventions with the victim and perpetrator. As MARAC meetings usually take place every four weeks, in some cases there had already been a repeat reported DVA event between the original referral and the meeting taking place. Once a case was discussed, any required actions were determined and recorded. All actions concluded from the MARAC meeting were emailed to all agencies following the meeting. An action tracker was sent with the actions to be completed by agencies and ensure actions were carried out and that there was a record of actions beings completed. Some of the agencies involved across both observed MARACs included police, health, mental health, CSC, Housing, Probation, and multiple local disadvantage teams. The MARAC observations showed how the information was used to determine the actions taken by agencies that are involved with the victim, perpetrator and family and therefore the level of safeguarding and intervention that is provided.

3.4.4. Data collected in the police response

Observations and interactions across the force demonstrated the complexity of the police response and the various stages and personnel involved. The information gained from these interactions with the force also highlighted the several points of data collection. Figure 3.9 shows a summary map of the police response. This section will describe some of the data sources that were identified, and provide the reasons for four of these to be selected as alternative data sources. The subsequent section summarises the reasons for these data sources to be reconstructed into a curated dataset using a measurement framework before they were suitable for analysis.

Table 3.9 Full police response map



Domestic abuse (DA) referral

The DA referral is a digital document that should be submitted by responding officers for every reported DVA event and shared with MASH. Standard fields in the referral include the name and address of the victim, suspect/offender, and any dependents or other persons relevant to the event or dyad, the location of the event, the date and time of the event, the DASH, whether the dyad are referred to MARAC, and the referral decision (e.g. Single Agency – Police, Single Agency – IDVA, NFA). The referral includes a free-text description of the event recorded by the responding officer(s).

To submit a referral, the referring officer must have identified that a reported event was related to DVA. A referral must have a lead referral attached who is the target of safeguarding, in DVA this is the identified victim, though they may not be named as a victim if the event was not classified as a crime. The referral form must also include a suspect or offender, and may include other persons related to the event such as children or witnesses. As these persons are required for a referral to be made, events that do not fit the DVA definition, such as crimes against businesses, are not captured in the sample, as they are in the recorded and flagged crime data that were extracted in the original police datasets.

As the DA referral should be submitted for all DVA events and includes information on both victims and perpetrators, referrals should capture repetition. The referral provides information on the victim and perpetrator, the event, and action taken by police, thus should provide information that enables the analysis of DVA patterns and police action, although much of this information is embedded within the free-text.

The amount and type of information recorded in the description is not standardised and is dependent upon the judgement of the recording officer on what is deemed relevant for MASH. MASH receive all referrals, review the risk and add information. The amount of information added to the referral by MASH varies by the risk classification. Standard-risk cases receive minimal review, and little information is added by MASH. For high-risk cases, MASH will complete multiple checks and populate the referral with information on the victim, perpetrator, dyad, and any dependents. For high-risk cases, MASH check for the victim and perpetrator on PNC and request information from PND to build a chronology of the victim and perpetrator's contact with the police. Information is shared with and sought from other agencies to add to the referral. The majority of the information added by MASH is free-text.

As stated earlier, since the observation of the MASH response there has been a new IT system implemented across the force. There has also been a force review of MASH, which changed some aspects of the MASH response and affected the data recorded in referrals. Telephone meetings were held a Detective Inspector within MASH and a MASH team leader to discuss the changes. The IT system was introduced in November 2018 and has changed the way the force record data and the way officers notify MASH of a DVA event. Frontline officers no longer submit a separate DA referral report. Instead, officers record an investigation and record any crime as they would with any other offence type, and then they must 'register an interest' for MASH within the investigation report. MASH receive the notification of interest and use the information that the police officer has entered into the investigation, rather than from a separate referral. MASH still review the case and conduct any additional checks. The DA referral has been replaced with a Police Safeguarding Report completed by MASH. The MASH review found that there were too many steps in the MASH response that were unnecessary or wasteful, largely due to a process-driven approach to reviewing cases. The actions taken followed a process-map and the taken steps of information seeking and sharing were dependent on the risk classification allocated to the referral. Following the review, the process-maps have been removed from the new referral system, and staff are encouraged to look at the case circumstances when making a decision rather than looking only at the headline e.g. 'Medium-risk DA'. These changes have not affected the data used for this study.

As the referral provides information on victims, perpetrators, events and the actions of the police and other agencies, the referral was selected as an ideal alternative source of data to measure the pattern of DVA repetition and police action. The referral contains event identifiers including an ILRN, and the CRN for crimed events, which can be used to identify these data sources in force information systems.

Incident report

Incident reports are opened for all events reported to the police. The incident report has a free-text timeline of the event as reported and the first police response, as recorded by the call-handler and responding frontline officers. Each free-text entry into the incident log is time stamped, providing a chronological order of the FCR and frontline response. Standard fields in the incident report include the address of the event, the date and time of the report, the police response grading allocated to the event, the number of officers attending, and the number of persons arrested. As incident reports should be available for all reported events, they would provide a way of measuring the repetition of events within the data if repeat cases were identifiable. However, incident reports do not record information on the victim or perpetrator as standard fields, thereby preventing the identification of repeat victims and perpetrators across incident reports. The incident code is a standard field for the incident report, though when this is ‘domestic incident’ or ‘domestic code’, the code provides little insight into what happened in the event. The free-text provides much more detailed information on the circumstances of the event and the action taken by the police in response. Though incidents cannot measure DVA repetition based on victims or perpetrators when used alone, the presence of an ILRN means information from the incident log can be linked to information in other data sources that also have an ILRN, namely the DA referral and the crime report. The incident report was therefore also chosen as a source of data to be included in the study.

Crime report

Crime reports are opened for crimed events. The crime report has a short free-text summary of the event and the actions taken by the police, including whether the case was sent to CPS and their decision. Standard fields in the crime report include the victim and the perpetrator name and address, the Home Office crime code and crime category, the police recorded outcome, the crime status, and any flags. Crime reports record more information on the type of event and on the action taken by police as standard fields than the incident reports. As the crime report contains identifiable information on the victim and perpetrator, these details can be used to identify the same victims and perpetrators across reports and provide some measure of repetition. However, as discussed earlier in the Literature Review and earlier in this chapter, crime data is a subset of the DVA that comes to police attention, as around half of DVA reported to the police does not result in a crime report (ONS, 2019a), thus half of DVA is excluded from the measure of repetition. The offence codes and standard fields of police and CJS action including the crime status and recorded outcome are useful measures of police action in some events of DVA. Though the crime report is limited in its measure of repetition and additional information on victims, perpetrators and the circumstances of the event, the report has an ILRN, which allows for the identification of the incident report and DA referral. The crime report was chosen as a source of data to be included in the study.

DASH risk assessment

DASH should be completed with the victim for all reported DVA events. The DASH has 27 questions designed to identify high-risk factors for serious violence and homicide and to determine the level of police intervention (Richards, 2009). The DASH assessment has 27 binary yes/no indicators for each question as standard fields, a short free-text response for each present risk factor, the allocated risk classification as a standard field, and a short free-text rationale for the risk classification decision. As each of the risk questions are standard fields, information on the history of violence between the victim and perpetrator are available as standard fields. The free-text fields with each question provide further information on the identified risk factor. The free-text rationale for the risk assessment given may provide insight into the police's use of discretion based on the presenting information, as well as providing information as to whether the risk assessment was refused by the victim. The DASH is linked in force information systems to the DA referral, thus each referral should have an associated DASH. DASH was therefore chosen as a source of data to be included in the study.

PNC

The PNC is a national system that stores information on individual's criminal records. Data from the PNC can provide information on individual's conviction history for all police forces in England and Wales. MASH use PNC to identify and extract the conviction history of the perpetrator and victim. The information is entered free-text into the DA referral. The amount and type of information extracted from PNC and entered into the referral is dependent upon the risk classification of the referral and the judgement of the referral assistant. Some referrals contain no PNC information, some include only convictions for violent offences, some include only recent convictions, and others include all convictions. The information extracted from PNC contains some of the required variables on the history of violence for the victim and perpetrator, though the information is embedded within free-text in the referral. The PNC may be selected as a source of data in its original form to measure crime and police activity. For the purpose of this study, only the information extracted by

MASH into the DA referral is included. The reason for using only this extracted data is access, as the researcher was granted access to the information systems of Lancashire Constabulary, and did not seek further access to the use of the PNC as this was deemed beyond the scope of the research.

PND

The PND is a national system that stores information on all contact between individuals and the police. PND contains conviction data, though unlike PNC also contains information on offences for which the person was not convicted, arrests, and any local intelligence on a person added by the police. For high-risk cases, MASH may add data from the PND. MASH referral assistants do not have direct access to PND and to add information requires a request to be made to the PND. The request must specify a period of time e.g. a request for two years of police contact information for the perpetrator. MASH add the information from PND to the referral as free-text. The information extracted from PND contains some of the required variables on the history of violence for the victim/perpetrator, though the information is embedded within the free-text in the DA referral.

The PND may be selected as a source of data in its original form to measure crime and police activity. For the purpose of this study, only the information extracted by MASH into the referral is included. The reason for using only this extracted data is access, as the researcher was granted access to the information systems of Lancashire Constabulary, and did not seek further access to the use of the PND as this was deemed beyond the scope of the research.

3.4.5. Reconstruction of police data to measure patterns of DVA and police action

Interactions with officers and staff across the force identified multiple data sources that contained information that could contribute towards analysis and therefore understanding of repeat DVA patterns and police action. From interactions with the police and mapping the response, four data sources were chosen: DA referrals, incident reports, crime reports and DASH. To measure patterns of DVA repetition requires information on all DVA events that are reported to the police, victims, perpetrators, the event and the actions that were taken by the police in response. This information is available throughout the four selected data sources. However, the data are spread unevenly across these four sources, and much of the information is embedded within free-text narratives and is therefore not directly extractable.

The selected data were therefore reconstructed into a new curated dataset. Information was manually extracted and recoded into a new quantitative dataset for analysis. The process of curating the data was intensive and iterative. The curation firstly required a testing phase to determine what information was consistently recorded across each of the forces, how the information could be categorised into suitable variables, and how the data could be combined from each source into one dataset. All extracting, recoding and input was done by the researcher. The curated dataset is one of the key outputs of the thesis, as it represents the ability of police data to capture patterns of DVA repetition and assess the influence of different police actions when the data are reconstructed into a measurement framework designed to measure DVA and police action. Due to the extensive and time-consuming task of data reconstruction, the resulting dataset is a small sample of the DVA that came to force attention, and serves as a pilot example of police data potential. The procedure for curating the dataset is presented in the subsequent Results One chapter to the thesis, following the measurement framework derived from the findings of the Literature Review and knowledge of police data and information systems gained from interactions with the police force.

Following the selection of the data, two of the key measures for measuring patterns of DVA repetition, frequency and severity, were defined. The defined measures were recreated in the curated dataset. The subsequent section of this Methodology chapter presents the methods considered and selected for defining frequency and severity.

3.4. Defining frequency and severity

The focus of the research questions is DVA repetition. As discussed in the Literature Review, DVA repetition is measured using both frequency and severity. Multiple measures were considered measure the frequency and severity. This section provides the method for developing frequency and severity variables.

3.4.4. Frequency

Frequency refers to the total number of events experienced by individuals or dyads and to the rate of events over time. In the curated dataset, frequency was examined for victims and for dyads. The structure of the curated dataset did not allow for the measurement of perpetrator frequency outside of their dyad. The number of events per victim and dyad were calculated within the curated dataset using the *aggregate* function in SPSS to calculate the number of times the same victim ID and dyad ID numbers appeared. The rate of change in frequency was examined for repeat dyads through latent trajectory analysis. Latent trajectory analysis produced categories of different trajectory shapes. The frequency trajectory classifications were added to the dataset as a new variable.

3.4.5. Severity

Severity is defined as the seriousness of each event and the rate of change in severity. There are multiple ways to consider and measure seriousness, and the measure will influence the rate of change. Different measures of severity were present throughout the Literature Review. In the discussions of police work and police data, it is recognised that one of the first actions the police can take is to record an event as a crime, as defined by the Home Office (2020a), which then triggers further action from the police and CJS. A crime could therefore be considered as an indicator of greater severity in comparison to a non-crime. Brimicombe (2016) demonstrated this distinction in his analysis of DVA escalation when allocating all non-crimed events the same severity score of zero, whilst crimed events were given a variety of different higher scores. Another distinction of severity commonly referred to throughout the DVA literature is whether a DVA event involves physical violence, and whether that violence results in physical injury to the victim (Walby and Towers, 2018). In existing research into DVA repetition in police data, the common measure of severity is the Cambridge Crime Harm Index (CHI), devised by Sherman et al (2016) (for example Bland and Ariel, 2015; Barnham et al, 2017).

These three measures were therefore considered as measures of severity in the present analysis. In addition, two more severity scales were added for comparison to the CHI. These are the offence seriousness scores (Francis et al, 2005) and the Home Office costs of crime harm index (CCHI) (Heeks et al, 2018). This section provides a summary of each measure and the method of adapting the severity measure to the data.

Crime and non-crime

All events reported to the police are recorded as an incident (Home Office, 2020a). The police then determine whether a crime has occurred and record the crime accordingly. Crime is defined by the law, the Home Office (2020a) provide a list of notifiable offences and rules for counting and recording crime. If the police believe the reported events amount to a crime by law, and if on the balance of probabilities i.e. the incident was more likely to be a result of crime than not, then the police should record the crime.

The distinction between incidents and crimes indicates that crimes are judged as more serious by the law. HMIC inspections into the integrity of police crime recording practices have found that some reported incidents do meet the criteria to be recorded as a crime, though are not crimed by police due to poor police data recording practices (Mayhew, 2014). Alternative reasons for non-criming of reported incidents include the pressure of police performance targets which motivates some recording officers to no-crime or downgrade reported incidents (Mayhew, 2014). Incidents are therefore referred to throughout this thesis as ‘non-crimed’ events as the circumstances of some non-crimed events may be similar to those of some crimed events. A binary variable was added to the curated dataset to code whether an event was crimed by the force. To consider the context of the event and the severity, a new variable was derived to describe the key circumstances of each non-crimed event (e.g. verbal altercation, threat, breach) (see Results One). The non-crimed event variable enabled the following severity measures to be applied to non-crimed events as well as crimed offences.

Violence with and without injury (Walby and Towers, 2018)

Walby and Towers state the seriousness of offences of domestic violent crime varies by the harm to the victim, and the more injurious events are the more serious. The DVA cases in the dataset are defined as DVA by the police force, and include incidents of any type reported to the force that were classified by the responding officer(s) as relating to DVA, and shared with MASH. The data therefore contain a range of violent and non-violent events. A variable was added to the dataset that defines events as non-violence, violence with injury, and violence without injury.

3.4.5.1. Severity scales

Severity scales assign a numeric score to an offence, with higher scores indicating greater severity. Each of the presented severity scales derived their scores from Home Office offence codes, which are defined by the act and the harm to the victim (Walby et al, 2017). Violence with injury scored higher in seriousness across all three indices[4] (shown in Table 3.7). As non-crimed events are not included in Home Office offence codes, each severity scale was adapted to the data in the curated dataset. A summary of each scale and the method of adaptation is given here.

Offence seriousness scores (Francis et al, 2005)

Francis et al produced a comprehensive set of seriousness scores for individual offences. The scores were computed using correspondence analysis of Home Office sub categories of offences by the sentence disposal for each offence. A variable was added to the dataset to assign a score to each event.

Though the set of scores is extensive, not all offences are included. Furthermore, the list of notifiable Home Office offences has changed since the scale was produced, therefore some new offences such as Controlling or Coercive Behaviour are not included. When an offence type appeared in the severity scale, the offence seriousness score was applied to the event in the dataset. For offences that were not included in the severity scale, the score of the closest equivalent offence in the seriousness scores was applied to the event in the dataset. For non-crimed events, the closest equivalent offence code was taken. For non-crimed events classified as 'verbal altercation' or 'other'

[4] Excludes some cases in Sherman et al's (2016) CHI. Where the offence is recorded only as 'assault with injury' and the level of injury not specified (e.g. ABH, GBH), the offence is given the common assault score of one. The injury does not increase the score in these cases.

in the non-crimed event type derived variable, which do not correspond to any offence, the case was given a seriousness score of zero. Examples of adapted scores are given below.

For crimed events of malicious communications, the closest equivalent offence in the index was taken to be ‘Cause harassment, alarm or distress’, with a score of three.

For all crimed events of other theft, the closest equivalent offence in the index was taken to be ‘Stealing not elsewhere classified’, with a score of four.

For crimed events in the dataset that were recorded with a major offence code rather than a sub-offence code, the lowest scoring offence within the offence category is applied. For instance, cases coded as ‘assault with injury’ or ‘assault without injury’ were given the common assault and battery score of four.

For non-crimed threats, the closest equivalent offence in the index was taken to be ‘Cause harassment, alarm or distress’, with a score of three.

For non-crimed breaches of any type, the closest equivalent offence in the index was taken to be ‘Breach of restraining order’, with a score of four.

Cambridge Crime Harm Index (CHI) (Sherman et al, 2016)

The Cambridge Crime Harm Index (CHI) assigns a score to Home Office offences based on the lowest starting point of sentence days a previously unconvicted offender could expect to receive if they were convicted for that offence. If the lowest sentence point is not served by number of days, the CHI converts the disposal into a number of days. For instance, if the lowest starting point is a fine, the CHI counts the number of days it would take to earn the amount of the fine, based on the minimum wage. The CHI provides scores for individual offences, and for the aggregate offence categories of homicide, GBH, ABH, assault, rape, sexual assault, robbery, burglary, vehicle, theft, damage and fraud.

A variable was added to the dataset that assigned a CHI score to each event. For non-crimed events, the closest equivalent offence in the index was taken. For non-crimed events classified as ‘verbal altercation’ or ‘other’, the case was given a seriousness score of zero.

Home Office Costs of Crime Harm Index (Heeks et al, 2018)

The Home Office CCHI differs from the previous severity scales as the index scores are derived from the estimated economic and social costs rather than offence disposals. Heeks et al estimate an average unit economic and social cost per crime, using Home Office offence categories. Three phases are considered in the estimation of costs: costs of the anticipation of crime, costs of the consequences, and costs of the response. Anticipation costs include defence and insurance; consequence costs include stolen property, emotional and physical harm, lost economic output, health services and victim services; response costs include the police and criminal justice system. Heeks et al then converted the estimated unit costs per crime into an index of crime harm.

Where an offence type in the DVA dataset was included in the index offences, the CCHI score was added to the event in the dataset. For crimed events not included in the index offences, the closest equivalent offence code was taken. For non-crimed events, the closest equivalent code was taken. For non-crimed events classified as 'verbal altercation' or 'other', the case was given a seriousness score of zero. Examples of adapted scores are given below.

No score is provided in the index for offences of stalking/harassment. The offence class for stalking/harassment offences is violence against the person (Home Office, 2020a). For any offence relating to harassment in the dataset, including malicious communications and breaches of any type, the lowest scoring violence against the person offence, 'violence without injury' score of 6.8 was applied.

For any crimed or non-crimed theft in the DVA dataset not included in the index, the lowest scoring theft in the index 'Theft from vehicle' was applied, with a score of one.

For any non-crimed threats event in the DVA dataset, the 'criminal damage – other' offence in the index was applied, with a score of 1.6. The non-crimed threats category does not distinguish between the type of threat made. The least severe form of threats offence was taken to be threat to commit criminal damage. The lowest scoring criminal damage offence in the index was therefore applied.

Comparison of severity scales

The seriousness scores for each offence category were compared across the three scales, shown in Table 3.10. For each scale, the most serious offence is homicide, followed by rape. The order of seriousness varies by indices for the remaining offence categories. Each scale was included in the analysis of event severity, though Heeks et al's CCHI was used when statistically modelling the changing trajectories of severity over time. Heeks et al was chosen as the CCHI accounts for a greater range of the economic and social costs of crime that are taken to be more reflective of the level of harm, and therefore the seriousness, of each crime than sentencing lengths and disposals.

Table 3.10 Seriousness scores by offence and indices

Offence	Francis et al 2005	CHI (Sherman et al, 2016)	Costs of CHI (Heeks et al, 2018)
Homicide	10	5,475	3699
Violence with injury	4 – 5	1 – 1,460	16.1
Violence without injury	5	1	6.8
Rape	8	1,825	45
Other sexual offences	3 – 6	365	7.5
Robbery	6	365	13.0
Burglary	4 – 7	20	6.8
Theft of vehicle	4	20	11.8
Theft from person	4	20	1.6
Theft other	4	2	1.0
Criminal damage – arson	4 – 5	33	9.7
Criminal damage – other	4 – 5	2	1.6
Fraud	5	20	1.5

3.5. Statistical analysis methods

The final phase of the research design was statistical analysis of the curated dataset to test the ability of the data to examine patterns of DVA repetition and police action. Two subsets of research questions were developed to structure the statistical analyses.

Patterns of DVA repetition

- Are victims female and perpetrators male?
- Does DVA escalate in frequency and severity?
- Do DVA trajectories compare with typologies identified in the literature?

Relationships between police actions and DVA repetition

- What action do the police take in response to DVA?
- Is there any association between the type of police action taken and the frequency of DVA?

- Is there any association between the type of police action taken and the severity of DVA?

This section of the chapter presents the statistical methods used to address each of the research questions, including a summary of the method and its application to the data.

3.5.1. Measuring the sex of domestic violence and abuse

To understand the sex distribution of DVA requires measurement of the prevalence, frequency and severity of events by and against female and male victims and perpetrators. Descriptive analysis was conducted in SPSS to measure events by sex. Prevalence was defined as the proportion of females/males in the victim/perpetrator populations. The data were aggregated by the victim ID to produce a victim subset of the data, and by the perpetrator ID to produce a perpetrator subset of the data. Descriptive commands produced the proportion of female/male victims and perpetrators. Frequency was defined as the number of events against/by female and male victims and perpetrators. The aggregate function counted the numbers of events by/against each victim/perpetrator. Descriptive commands produced the total and average number of events by/against females/males to compare the frequency of DVA by sex. To measure severity, all five measures of severity were used. Descriptive commands produced the proportion of events that were crimed, the proportion of events that were violent, and the range and average seriousness scores for female and male victims and perpetrators using each severity scale.

3.5.2. Measuring escalation

Escalation was defined as increasing frequency and/or increasing severity. The analysis first examined whether there was any change in frequency and/or severity between repeat events, and then looked at the shape of change over time. For measuring escalation, the dyad was the unit of measurement. By focusing on the dyad, any identified changes should reflect changes in the frequency and severity of DVA between the same victim and perpetrator, and patterns should not be affected by changes to the dyad, such as a victim having a new partner.

3.5.2.1. Identifying escalation

Change in frequency and severity was first examined using descriptive commands of five derived escalation variables and the risk classification variable (see Results One). The five derived variables code yes or no to the following questions, derived from DASH:

Is the abuse happening more often?

Is the abuse getting worse?

Has the perpetrator ever used weapons or objects to hurt the victim?

Has the perpetrator ever threatened to kill the victim or someone else?

Has the perpetrator ever attempted to strangle/choke/suffocate/drown the victim?

The proportion of events that were coded as yes for each escalation variable was computed for the first and last events for repeat dyads. The proportion was compared to show whether more dyads have identified escalation in the last event than the first, therefore indicating change in frequency and/or severity between the first and the last recorded event. This was repeated for the risk classification variable to compare the proportion of first and last events for repeat dyads that were classified as standard, medium and high-risk. This method could only identify whether there was any evidence of change between the first and last recorded DVA event, and could not signify any fluctuations in frequency and severity between the two recorded events.

3.5.2.2. Measuring the rate of change over time

The rate of change in frequency and severity for repeat DVA was then examined. The rate of change refers to the extent to which repeat DVA increases or decreases in frequency and/or severity over time. The rate of change was first looked at using descriptive trajectory analysis, and then tested statistically through latent trajectory analysis.

3.5.2.2.1. Descriptive trajectories

The aim of the descriptive trajectory analysis was to visually compare the trajectories of each repeat dyad, and to manually consider whether there were similarities in dyad trajectory shapes. A dyad trajectory can be understood as a visual path of the series of DVA events recorded for the dyad. The descriptive analysis was conducted in Microsoft Excel. All dyads with two or more recorded events (n=51) were included. Some victims appear in more than one dyad due to experiencing DVA by multiple perpetrators. For each dyad, all recorded events were plotted by date and severity score to produce a trajectory of escalation. To produce the plots, the dyad ID number, date that the DA referral was submitted and severity score was read into Microsoft Excel. The measure of severity used in the descriptive analysis is the three-point non-violence to violence with injury variable:

1. Non-violence

2. Violence without injury

3. Violence with injury

For each dyad, the severity score of each event was plotted by the date that the event was reported to the police. This produced a visible trajectory of the frequency and severity of repeat DVA events. All dyad trajectories were visually compared and manually placed into categories of similar trajectory shapes. The trajectories are presented beneath their manual trajectory classifications in Results Two.

3.5.2.2.2. Latent trajectory analysis

The shape of change in repeat DVA was modelled statistically using latent trajectory analysis. The aim of latent trajectory analysis is to identify distinct clusters or groups of cases in a dataset that have similar trajectories (Nagin, 2005). In this analysis, latent trajectory models were used to determine whether distinct groups of dyads with similar trajectories of frequency/severity could be found. Latent trajectory models are a type of mixture model (Nagin, 2005). The model specifies that the data be composed of a mixture of unobserved groups. Latent trajectory analysis estimates the parameters of the groups using maximum likelihood estimation. A separate set of parameters measuring the expected frequency/severity of DVA at each time-point were estimated for each group. The parameters defined the shape of the trajectories and the probability of a dyad belonging to a particular trajectory group.

The frequency and severity trajectory groups were estimated separately. Frequency was measured as the number of events within a specific time-point, estimated over a series of time-points. Severity was measured as the adapted CCHI (Heeks et al, 2018) score, estimated for each event. The frequency model treated frequency as a count variable. The distribution used for modelling count data is the Poisson distribution. The model is applied to count data. The severity model treated the severity score as an ordinal variable, this is also modelled with a Poisson distribution. Formally, this is written as:

$$p^i(y_{it}) = \frac{\lambda_{jt}^{y_{it}} e^{-\lambda_{jt}}}{y_{it}!} \; (y_{it} = 0, 1, 2, \ldots).$$

(Nagin, 2005).

The equation specifies the probability of y_{it}, that is a dyad at time *t*, equalling any non-negative integer value (Nagin, 2005). In other words, the probability of a dyad equalling a specific value at a specific time-point. The probability assigned to each possible outcome depends on the mean rate of occurrence of the event for all dyads in a given group j at each time t (Nagin, 2005). The rate is denoted by λ_{jt}. When estimating frequency in the DVA data, λ_{jt} measures the expected number of events in a given time-point for all dyads belonging to group *j* at time *t*. When measuring severity in the DVA data, λ_{jt} measures the expected severity score per event for all dyads belonging to group *j* at time *t*.

The model predicts what the frequency or severity would be at any given time-point. As the relationship between time, and the frequency or severity, is not linear, a transformation a log transformation is appropriate. This model is written as:

$$log(\lambda_{jt}) = \beta_{0j} + \beta_{1j}t + \beta_{2j}t^2 + \beta_{3j}t^3$$

The equation shows a log-linear model in cubic time for each trajectory *j*. The λ_{jt} represents the dyad λ_j at time *t*. The β_{0j} represents the intercept, the expected mean value of frequency or severity, and the coefficients β_{1j}, β_{2j} and β_{3j} are the regression coefficients for the group j cubic polynomial for group *j*.

Multiple models were estimated to determine the optimal number of trajectories in the data. Each model fits a different number of trajectory groups to the data. In both analyses, six models were estimated, each fitting between one and six classes to the data. To determine which model is the best fit and which number of groups best describes the data, the main goodness-of-fit test is the Bayes Information Criterion (BIC) (Nagin, 2005). Each model produced a BIC value. The model that had the greatest decrease on the BIC indicated the best fit to the data.

In addition to BIC, the optimal model can be assisted with the interpretability of the given trajectories, and the posterior-group membership probabilities (PGMP). The interpretability of the model refers to whether the number of given groups makes sense in the context of the subject area. The aim of choosing the model is to reduce the number of groups without missing any important or distinct groups, selecting the model with 'no more groups than is necessary to communicate the distinct features of the data' (Nagin, 2005: 77). PGMPs assess a dyad's likelihood of belonging to a specific group and can be used to assess model fit. PGMP differs to group membership probability. The probability of group membership is the proportion of individuals/dyads that are assigned to a group. PGMP is the probability of a specific individual with a specific profile belonging to a specific group *j*. A PGMP of one is the best indicator that the dyad has been allocated to its 'correct' group. To assess the accuracy of PGMP, Nagin applies a cut-off of 0.7. If a dyad has a PGMP of 0.7 or above, they are likely to have been allocated to the 'correct' group. The PGMPs for each dyad in each trajectory group were considered to assess model fit.

Formatting

All analyses were conducted in LatentGOLD software v 4.5. Data were formatted for analysis in SPSS The data were filtered to only include dyads with two or more events. Where victims appear in multiple dyads, the most recent repeat dyad was taken. Earlier dyads relating to the victim were deleted from the dataset. This sought to ensure that any fluctuations in frequency/severity reflected changes in the DVA between a dyad, rather than showing effects of changes in perpetrator. Two datasets were derived, one for frequency and one for severity.

For the trajectory analysis, frequency was measured as the number of events recorded for each dyad in a specific time-point. As the focus is on repetition, the data were firstly filtered to only include dyads with two or more events (n=51). For victims with multiple dyads, the most recent repeat dyad was taken and previous dyads are omitted from the data (n=20). Additional dyads relating to the same victims were omitted to account for any possible relationship that one dyad may have on another dyad's trajectory, and to allow for the analysis of individual characteristics of victims in each identified trajectory later in the analysis.

The data contained dyads with various complete and incomplete trajectories of different lengths. The range is shown in Table 3.11. In the full dataset, the time between the first and last recorded DVA event varied from a minimum of 22 days and a maximum of 7.5 years, the number of recorded events varied from 2 and 18, and trajectories started and ended at different points within the dataset time-period, some multiple years apart.

Table 3.11 The range in the number and time between events for repeat dyads in the full dataset

	Minimum unit	Maximum unit
Time between events	22 days	7.5 years
Number of events	2 events	18 events

To align the dyad trajectories, the first recorded event for each dyad represented the start of the first time-point. To capture as much data as possible whilst maintaining a manageable number of time-points in the data, a follow-up period of three years was selected, with each time-point representing a six-month period. Six-month periods were selected pragmatically to cover the three-year period with a manageable amount of time-points. Three-years was selected to align the dyads whilst retaining the majority of data, and to be consistent with previous research in this area (see Bland and Ariel, 2015; Brimicombe, 2016). There were therefore six time-points in total for each dyad. If there was more than three years between the first and second recorded event, the dyad was omitted (n=1).

This left **30 dyads** eligible for the analysis. Six time-point variables were added to the frequency dataset. For each event, if the incident date fell within a specific time-point, that time-point variable was coded as one. If a dyad trajectory exceeded three years, the later events were omitted from the analysis.

The data were aggregated by dyad ID to sum the number of events in each time-point for each dyad. If a trajectory was shorter than three years, due to the three years surpassing the end of the study period, the later time-points were recorded as missing. If a trajectory in the data crossed a time-point though did not complete it, any events that were recorded in that time-point were counted. Partially missing data were therefore included.

An example is:

Dyad 15a

The first recorded event for the dyad is 6^{th} December 2017. A full three-year trajectory for the dyad would therefore be 6^{th} December 2017 – 6^{th} December 2020. In time-points, this would be:

0 – 6 months: 6^{th} December 2017 – 6^{th} June 2018

6 – 12 months: 7^{th} June 2018 – 6^{th} December 2018

12 – 18 months: 7^{th} December 2018 – 6^{th} June 2019

18 – 24 months: 7^{th} June 2019 – 6^{th} December 2019

24 – 36 months: 7^{th} December 2019 – 6^{th} June 2020

The end of the study period is 16^{th} November 2018. The time-point for 6-12 months is therefore partially missing, as the dates exceed the study period. The events in this time-point are counted, thus the partially missing time-point is included. The remaining time-points that all exceed the study period are recorded as missing and excluded from the trajectory analysis.

The data were restructured into long format, to produce a dataset with six rows for each dyad, an index time variable (1… 6) and a frequency variable that coded the number of events the victim had in each time-point. Quadratic (*Time2*) and cubic (*Time3*) time variables were added to the dataset. Table 3.12 gives an example of a dyad in the dataset.

Table 3.12 Structure of frequency dataset for latent trajectory analysis

Dyad ID	Time	Time2	Time3	Frequency
13a	1	1	1	1
…				
13a	5	25	125	0
13a	6	36	216	0

The same subset of 30 dyads was used in the severity analysis. Severity was measured for the analysis as the adapted CCHI score (see section 3.4.4.2) per event. Each event represents a time-point. The maximum number of events experienced by a dyad in the dataset is 18. In the severity dataset, 18 time-point variables were added. For each number event in a dyad series, the CCHI score was added to the time variable. For dyads with less than 18 events, the additional time variables were coded as missing. There are no partially missing data in the severity analysis. The data were then restructured into long format, to produce a dataset with 18 rows for each dyad, an index time variable (1… 18) and a severity variable that coded the CCHI score for each event for each dyad. Quadratic and cubic time variables were added to the dataset. Table 3.13 gives an example of a dyad in the dataset.

Table 3.13 Structure of severity dataset for latent trajectory analysis

Dyad ID	Time	Time2	Time3	Severity
15a	9	81	729	0
…				
15a	12	144	1728	1.6
15a	13	169	2197	-

Model estimation

Both datasets were read into LatentGOLD 4.5. For each analysis, six regression models were estimated with one – six classes. The frequency/severity variable was the dependent variable, predicted by time, quadratic time and cubic time. For the frequency analysis, the dependent variable was modelled as a count variable. For the severity analysis, the severity dependent variables was modelled as an ordinal variable. The model applied 100 start values and 50 iterations. The model excluded missing values.

The estimated values and PGMPs were selected as output. The estimated values were plotted in Microsoft Excel to produce trajectories. The BIC values, PGMPs and interpretability were considered to select the best fitting frequency and severity model to the data. The results of the latent trajectory analyses are presented in Results Two.

3.5.3. Comparing trajectories against typologies of domestic violence and abuse

Theories of DVA discussed in the Literature Review contest whether there are different forms of DVA, and whether there are characteristic differences between the different forms of DVA. The characteristic differences focus particularly on gender, violence and escalation (Johnson, 2008; Walby and Towers, 2018). To compare the trajectories identified in the descriptive and latent trajectory analyses, descriptive commands were used in SPSS to compare the presence of particular characteristics in each trajectory group, such as victim and perpetrator sex, relationship, and employment status. The characteristics of trajectory groups were compared for the four trajectory classification derived from the descriptive trajectory analysis, and for the frequency trajectories estimated in the latent trajectory analysis. Pearson Chi-Squared tests examined for any significant association between the selected individual and dyad characteristics and trajectory classification. No more than one severity trajectory was identified in the latent trajectory analysis, thus characteristics were observed for the full data sample rather than compared across different severity trajectories. The results of the descriptive analysis of trajectories are presented in Results Two.

3.5.4. Measuring police actions in response to domestic violence and abuse

Police action was defined by the measures available in the data. The available measures included response grading, risk assessment, arrest, referral to another agency, and police identified outcome (see Results One). Not all types of police action were available in the data. Descriptive commands in SPSS produced the proportion of actions taken by the police in response to different types of crimed and non-crimed events. Pearson Chi-Squared tests identified any significant correlations between the type of event and the type of police action taken. A correlation describes the strength of a linear relationship between two random variables, and does not assume that one variable predicts the other (Casson and Farmer, 2014). The results are presented in Results Two.

3.5.5. Assessing the relationship between police action and the repetition of domestic violence and abuse

To test for any identifiable relationship between police actions and repetition, the analysis separately looked at DVA frequency and severity. Frequency was examined as the shape of change over time using the trajectories identified in the latent trajectory analysis, and then as the average frequency rate per year per dyad. Severity was measured as the mean event severity experienced by a dyad. The relationship between police actions and the shape of change in severity was not investigated as distinct trajectories were not identified in the severity trajectory analysis (see Results Two).

The relationship between police action and the changing rate of frequency was examined using descriptive analysis. Descriptive analysis looked at the types of police action experienced by dyads in each of the frequency trajectory groups (section 3.4.4.2). Pearson Chi-Square tests determined whether there were any significant associations between police action and frequency trajectories.

The final phase of analysis examined whether there was any significant relationship between the available measures of police action and the frequency rate of events experienced by a dyad per year, and the mean severity of events experienced by a dyad, using forms of regression analysis.

3.5.5.1. Descriptive analysis of police action and frequency trajectory groups

The measures of police action used in the descriptive analysis included whether the perpetrator had ever been arrested and whether the dyad had ever been referred to another agency, disaggregated by the types of agencies included in the data (probation, IDVA, health, mental health, education, Children's Social Care (CSC), Adult Social Care (ASC) and substance misuse) (see Results One for variables). The frequency dataset of 30 repeat dyads derived for the latent trajectory analysis was used. For each dyad, there was a categorical variable that codes which of the frequency trajectory groups the dyad was assigned to. Descriptive commands compared the percentage of dyads in each trajectory group that received each of the police actions. The analysis did not specify at what point in the trajectory the dyad experienced the police action, nor how many times the dyad received the police action. Pearson Chi-Squared tests determined whether there was any significant association between the police action variables and the trajectory group classification.

3.5.5.2. Regression analysis of police action, frequency and severity

The final stage of the analysis examined whether any measures of police action could significantly predict the frequency rate of events experienced by a dyad, and the mean severity of events experienced by a dyad. Two regression models were fitted to the data.

Regression models aim to explain variations in a dependent variable using a model of explanatory variables (Field, 2013). For continuous dependent variables, as the mean severity score was treated, a simple linear regression model can be fitted. The linear regression model can be written as:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \qquad \text{with } \epsilon \sim Normal(0, \sigma^2)$$

In the equation, β_0 represents the intercept; β_1 represents the rate of change or slope in the dependent variable, denoted as y_i, for every unit change in x_i. The error of the model is represented by ϵ_i. The second part of the equation shows the normal distribution assumption. One of the key assumptions of the linear regression model is that the dependent variable, in this case the mean follows a normal distribution (Field, 2013).

Where the dependent variable is a count or a rate, a Poisson log-linear model is considered to be more appropriate than a simple linear regression. A Poisson regression model is generalised form of linear regression analysis used to model count data. Like with linear regression, there are two sets of data: the response count or rate which is the dependent variable, and a set of explanatory variables. The dependent count or rate variable follows the Poisson distribution.

The Poisson distribution is noted as:

$$Y_i \sim Po(\lambda_i)$$

The rate parameter is λ_i which is specific to an individual observation, which is related to the set of explanatory variables.

As the relationship between the explanatory and the dependent rate variable is non-linear, a link function is added to transform the non-linear relationship into a linear form. The Poisson log-linear model is written as:

$$log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

In the equation, *y* is the response variable, here the frequency rate, β represents numeric coefficients, β_0 is the intercept, and x is an explanatory variable.

The frequency regression model was first fitted. To measure the frequency of events experienced by dyads depends on the length of time that the dyad is observed, and there was considerable variation in the observation times of the dyads in the dataset. To align dyads, frequency was modelled as the *rate* of events per year. The rate was calculated prior to the model being fitted, as the average number of events recorded against a dyad per year, using a two-year average. A two-year average was chosen to increase the representativeness of the estimate for the dyad compared to taking the number of recorded events in the first year, without omitting even further dyads from the analysis, which would be required if the rolling average was increased to three or more years. The inclusion criteria for the regression analysis were all dyads with two or more events recorded within a two-year period (n=51). To get a two-year average for each dyad, only dyads that were able to have a full two-year trajectory in the data were included. As the final date of the study period is 16th November 2018, only dyads whose first recorded event was on or prior to 16th November 2016 were included. This omitted 12 dyads. A further five dyads were omitted due to having a gap of more than two years between the first and second recorded event. This left a sample of 34 dyads eligible for analysis.

Dyads with the same victim across more than one dyad were included in this analysis. The frequency rate variable was calculated by dividing the total number of events recorded for each dyad by two, to give an estimated number of events per year. Two years of data were taken from the first recorded event for each dyad. Events that were recorded outside of the first two years of the trajectory were omitted from this analysis.

For consistency, the same subset of dyads was included in the severity model. In the severity model, the dependent variable was the mean severity score of an event for that dyad. One of the key assumptions of linear regression is that the dependent variable, here the mean severity score, follows a normal distribution (Field, 2013). Several tests were conducted in RStudio to determine whether the mean severity variable followed a normal distribution, including a histogram and density curve, a QQ plot and a Shapiro-Wilk test (Karadimitriou, n.d). Both graphical tests indicated that the frequency variable did not follow a normal distribution. The Shapiro-Wilk test gave a p-value above 0.05, indicating that the variable did not follow a normal distribution. There are several approaches to dealing with then non-normality of the response variable such as variable transformations, or non-parametric tests (Pek et al, 2018). It was felt that the effects of transforming the response variable would be minimal to the interpretation of the results, and thus perhaps beyond the scope of this analysis. Future research may consider using alternative approaches to the non-normality of the response variable, or use data of a much larger sample size that has more allowance for breaches of the normality assumption.

3.5.5.2.1. Estimating models of DVA frequency and severity

Both models were estimated in R and RStudio v 3.5.1. The data were into RStudio using the *haven* package (Wickham and Miller, 2020). All variables (Table 5.65), excluding frequency/severity, were converted into factors.

To build a predictive frequency model, the frequency rate was treated as the dependent. To find the best fitting model, a forward selection procedure was used, with each explanatory variable added to the model individually to test whether the variable had a significant effect on the number of events per dyad. All explanatory variables used in the regression analysis is presented in Table 5.65 in the Results Two chapter. If the explanatory variable was not significant, it was removed from the model and the next variable was added and tested. If the variable was significant, the next variable was also added to the model and tested. This was repeated until all variables had been tested for significance and there was a final model of only significant explanatory variables. Significance was tested using p-values and a 95% confidence level. For the Poisson frequency model, a goodness-of-fit test was performed looking at the residual deviance, the difference between the deviance of the fitted model and the maximum deviance of the ideal model. A Pearson chi-square test determined whether the difference was significant, and thus whether the model was a good fit to the data.

To build a predictive severity model, the mean event severity was treated as the dependent variable. A forward selection procedure determined the best fitting model to the data. The dependent variable was tested for normality prior to the model fitting. Whilst these tests indicated that the mean severity score did not follow a normal distribution, the mechanisms to transform this variable were judged to make little difference to the results of the model and thus be beyond the scope of this analysis.

3.6. Ethics

Lancaster University Faculty of Arts and Social Sciences (FASS) Research Ethics Committee granted ethical approval for the project. The application for ethical approval was in two components. The first component sought approval for the field-work stage of the project. This stage involved observations of the police response and meetings with officers, staff and partner agencies. The second component sought approval for the extraction and quantitative analysis of secondary data collected by the police force. Several ethical considerations arise from both the qualitative and quantitative components of the research design, including informed consent of those observed, physical risks to the researcher posed by the observations, and the confidentiality of all data extracted from the force. The ethical considerations are addressed here through data access and data management.

3.6.1. Data access

The study was an ESRC CASE studentship with the researcher, Lancaster University and Lancashire Constabulary. A CASE studentship is a collaborative project co-supervised by a non-academic partner institution. As part of the studentship, the researcher was embedded into the force as an associate staff member and allocated a non-academic partner supervisor from the police force. There was a contractual agreement between the researcher, the university and the police force that details all terms, including access to the force and the intellectual property of resulting data and findings from the study. As part of the agreement with the force, the researcher was granted access to police force personnel, space and information systems. The relationship between the institutions and access to the police force was negotiated by the supervisory team prior to the commencement of the project. The researcher and supervisory team were all made associate staff members of the police force and allocated with associate staff identify cards. This required that the researcher and supervisors completed level 3 force vetting.

For observations, access to each site was facilitated by the force supervisor with a senior officer or staff member at each site. The researcher then arranged the observation with the senior officer/staff member. The force ID card allowed the researcher access into force buildings. All observations were overt and informed consent was given verbally or via email by both the force supervisor and the senior officer/staff member in each site on behalf of all police officers and staff members involved in each observation site. For instance in the ride-alongs, consent was given by the OIC for the frontline officers on that shift, and for MARACs, consent was given by the MARAC coordinator on behalf of all participants of the MARAC. For observations that involved shadowing individual staff members, such as the ride-alongs and MASH observation, verbal informed consent was gained from the individuals observed. Each officer and staff member was aware of the observation and that the information gained from the observation would contribute towards the research.

To access data stored in police information systems, the researcher was allocated a force laptop that provided remote access to force systems. To log into the laptop required a force ID card, pin and password. The researcher was given a force email address to communicate internally and share data. The researcher's level of access in the force allowed access to certain systems from which data could directly be extracted. To access additional data from systems that required higher levels of access, the force analyst extracted the requested data.

Information gathered from observations and meetings with the police and all data extracted from police systems were treated as confidential. The confidentiality of the data throughout data collection, analysis and dissemination was agreed between the researcher, the university and the police force in the contractual agreement of the study, signed by myself, the Detective Superintendent of the force PPU, and a university representative. The researcher and supervisors all signed the Official Secrets Act. All data were stored in line with a data management plan to ensure data were confidential and kept in accordance with the EU General Data Protection Regulation (GDPR) and Data Protection Act.

3.6.1.1. Physical risks to the researcher

Gaining access to some areas of the force presented additional risks to the researcher. The observation site that presented potential risks of physical harm to the researcher was the ride-along with frontline police officers. The ride-alongs involved the researcher being in a vehicle driving at high-speeds, and potentially witnessing crime whilst officers attend scenes. The risks to the researcher were physical harm from being in a high-speed vehicle and physical harm from violent events attended by the frontline officer. The police force were aware of the risks to an observer of frontline patrol and as such have an additional risk assessment that were completed on site with a

Police Sergeant (PS) and the officers being observed. Ride-alongs are common in this type of research, and the police are trained to ensure non-police observers are kept safe. Police officers are highly trained to drive safely at high-speeds, reducing the risk of physical harm to the researcher. The frontline officer risk assessed each event attended, and for emergency responses to violent events, the researcher remained in the locked police vehicle whilst the officer attended to minimise the risk of physical harm.

3.6.2. Data management

The data management plan details the types of data collected for the research project and the method of analysing and storing data in line with the contractual agreement, GDPR and the Data Protection Act. Two types of data were collected for the study. The first was primary data collected during observations of the police response, the second was secondary data extracted from force information systems.

3.6.2.1. Field-notes

To collect information from observations of the police, free-hand notes were made in a physical research journal during and following each observation. Police officers and staff were aware of the notes being made and understood that they would inform the research. The notes focused on the response processes and no identifiable or sensitive information relating to the force or members of the public was collected in the field-notes. To minimise disruption to the police, field-notes were only made when felt appropriate in the context of the observation (Reiner, 2000; Gravelle and Rogers, 2014). Following the observation, the field-notes were typed up and stored in an encrypted folder within Lancaster University's online file storage system. The storage system at the time was Lancaster Box, though has now moved to OneDrive.

3.6.2.2. Secondary data

Secondary data were extracted by the force for the project and the raw data files were sent to the researcher via internal force email. These data were used for the descriptive analysis of existing police datasets. Secondary data were also extracted by the researcher directly from force information systems using the force laptop. All raw data that contained identifiable information about members of the public, police officers and staff remained stored on the Home Directory/H: Drive of the force. The H: Drive was accessible only via the force laptop allocated to the project or other police force computer systems. All force computer systems require police username and password for access.

The data extracted by the force contained identifiable information on victims, perpetrators and associated persons in the form of names, dates of birth and addresses. To ensure data were confidential and could be stored outside of force information systems, all identifiable information was removed. All names and addresses for victims and offenders were replaced with unique numeric identifiers to match repeat individuals whilst removing identifiable information. All identifiable information and free-text fields were then deleted from the data whilst the data is still stored within police information systems. The de-identified data were sent via internal email to the force analyst to ensure the data met force standards of confidentiality and could be removed from force information systems. The de-identified data were then stored within an encrypted folder on Lancaster University's online storage system.

Data extracted by the researcher from force information systems were stored within the Home Directory/H: Drive of the force. The raw data were stored on the force laptop. Information from the raw data was manually recoded and entered directly into a blank SPSS dataset on the researcher's laptop. The SPSS dataset was stored within Lancaster University's internal storage systems. Each victim, perpetrator and dyad in the raw data was given a numeric identifier. The numeric identifier and the name of the individual(s) were entered into an ID index in Microsoft Word, saved within the force laptop. When entering the data directly into the SPSS dataset, the numeric ID number was entered, no identifiable information was ever entered. When analysing the context of non-crimed events, the free-text fields in the raw data files were analysed. To save these free-text fields, sections of the free-text were manually re-typed into a Microsoft Word document on my personal laptop without any of the identifiable information. Any reference to names, addresses, towns or any other identifiable information was kept on the force laptop and not transferred to the document. The de-identified document was stored in an encrypted folder on Lancaster University's online storage system. The encrypted folder was only accessible by the researcher through a password protected laptop and institutional account. As per the contractual agreement between the researcher, Lancaster University and the police force, any resulting intellectual property, such as the curated dataset, belongs to the university.

3.7. Conclusion

This chapter presents the methodology for the research, including the data and techniques of statistical analysis. In outlining and reviewing the existing sources of police data, this chapter starts to address the first two research questions of the thesis:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

The methodology starts with an outline of the existing data sources that were extracted from police information systems in discussion with Lancashire Constabulary. Four quantitative datasets were extracted directly from force systems using existing standard fields: recorded crime, offenders, incidents and DASH referrals. The extracted information produced large datasets, with some information on victims, and/or offenders, events and police action. The process of formatting these data and exploratory descriptive analysis deemed these datasets unsuitable for measuring patterns of DVA repetition. The key issues identified in these existing datasets were inconsistent recording of personal details, different units of measurement, problematic use of DVA identifiers and the presence of multiple DVA identifiers, and the embedding of information within free-text narratives. As these data were deemed unsuitable, alternative data sources were sought.

Alongside the extraction of the initial datasets, the researcher conducted a series of observations and interactions to discuss and map the police response and data recording practices. Information gathered from these interactions identified multiple data sources with rich information on victims, perpetrators, events and police action that could assist the measurement of DVA repetition. The four selected data sources were DA referrals, incident reports, crime reports and DASH. As these sources were of different formats and much of the information was not directly extractable due to the quantity of free-text, the data were reconstructed into a new curated dataset. This dataset and associated measurement framework provide a key output of this thesis, and the procedure for deriving the dataset is presented in the subsequent Results One chapter.

The remainder of the Methodology chapter presented the statistical analysis techniques used on the curated dataset to test the ability of police data to measure patterns of DVA repetition and police action. The analysis is structured on debates within DVA theory and policing drawn from the Literature Review and is tested through two subsets of research questions on the nature of DVA and whether police action has any effect on DVA repetition. The results of the statistical analysis seek to demonstrate the potential of police data, these results are presented in the Results Two chapter.

4. Results One: Presenting the measurement framework and curated dataset

4.1. Introduction

The thesis has three research questions:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

The previous chapter presented the methodology for the thesis, including the data sources considered and selected for use in this research, thus starting to address the first two research questions. The project started with exploratory analysis of four existing police datasets extracted from information systems. These quantitative datasets contained recorded crime data, offenders, incidents and DASH. Though the datasets held some of the sought after information for examining patterns of DVA repetition and police action, the structure of the data meant that the data were unsuitable for identifying patterns of DVA.

Observations of the police identified four alternative data sources that could address some of the issues identified in the original police datasets. The alternative data sources are: DA referrals, incident reports, crime reports and DASH. A description of each data source is given in the Methodology chapter. Though these sources collectively contained much of the sought after information, the data sources could not be used in their current form as they all came in different formats and were embedded within different systems. Much of the information in each of these sources, especially the DA referral, was free-text and non-standardised, making extraction of any measures difficult. To test the capacity of police data to measure patterns of DVA repetition, the four data sources were therefore reconstructed into a new quantitative dataset. The curated dataset follows a measurement framework derived from the Literature Review and knowledge of the police response and information systems gained through interactions with Lancashire Constabulary. The curated dataset provided the site for a pilot statistical analysis of DVA repetition and police action. The results of this analysis are presented in the Results Two chapter. The Results One chapter will firstly outline the measurement framework used to derive the curated dataset, and the method of curating the dataset.

4.2. Refining a measurement framework

The Literature Review identified features of DVA that were required for measuring and understanding patterns of DVA, and therefore testing some of the key debates. These included information on victim and perpetrator (e.g. gender, relationship) and individual and social factors that could interact with DVA repetition (e.g. socioeconomic status, mental health, previous violence). To understand repetition requires measures of frequency and severity, and to consider whether actions taken by the police have any impact on DVA repetition requires information on police action. The key data features for DVA and police action are presented as a measurement framework in Table 4.1. The framework is based on the features in the literature, and knowledge of police data and information systems, taken from observations and interactions with the force.

The variables are presented as they would be treated to measure the impact of any police action on DVA repetition. The first row is police action, of which measures would be treated as explanatory. Variables that were available in the data include the response grading, risk assessment, arrest, referral to other agencies, referral to MARAC, the charge of the perpetrator and police disposals given. The examples of police disposal given in the framework include offender cautions, DVPN/DVPOs and non-molestation orders. The latter two examples were not included in the data used for this research, but are included in the framework as examples of what information could be found in similar data sources used by other forces, and what should be included if so. These examples of police action do not exhaust the many possible actions taken by the police in response to DVA, but reflect some of the key features discussed in the Literature Review such as arrest (Sherman et al, 1992; Hoyle and Sanders, 2000) and risk assessment (Robinson et al, 2016; Almond et al, 2017; McManus et al, 2017), as well as the availability of information in the data.

The second row focuses on the measurement of repetition, which when assessing the impact of police action would be the dependent variable. DVA repetition is considered through both frequency and severity (Walby et al, 2017). As stated in the Methodology, measures of frequency and severity were defined for this research, using both the number and rate of events to measure frequency, and deriving severity scores using offence types and non-crimed event types to measure severity.

The next two rows look individually at victim/perpetrator. There are measures for sex, employment status, housing, mental health, physical health, alcohol/substance use and history of violence. Employment status and housing type are treated as the measures of socioeconomic status available in police data. Each of these measures has been identified in the literature as having some association with patterns of DVA (Barnish, 2004). For the victim, the history of violence refers to their history of DVA victimisation, this may be individually and within a dyad. For the perpetrator, the history of violence may refer to their history of DVA offending both individually and within a dyad, as well as wider history of violent offending taken from police records. The following row is the dyad. This again looks at the history of violence, focusing on the number of events relating to the same dyad within police records. Additional variables relating to the dyad are the relationship between victim and perpetrator, whether the dyad have any children or dependents together and whether the dyad live together.

The final row relates to the event. These measures focus on describing the nature of the event that took place. For crimed offences this may be the code applied by the police. For non-crimed, this needs to be a different code that captures the nature of the event, in other words a code that provides more information than ‘domestic incident’ or ‘domestic crime’. The final measure named ‘event components’ refers to a set of measures that code all of the event types that took place within the same event e.g. such a set of measures could capture whether one event included both an assault and threat to kill. This multiplicity of events is not captured by offence codes, which use a hierarchy of offences to apply only one offence code, even if one event involved multiple offence types (Home Office, 2020a).

Table 4.1 Measurement framework for measuring DVA repetition and assessing police action

Category	**Required variables**
Police action	Response grading
(Explanatory)	Risk assessment
	Arrest
	Referral to other agencies
	Referral to MARAC
	Charge of perpetrator
	Police disposal
Repetition **(Dependent)**	Event frequency (number of events, date of events)
	Event severity (severity score derived from offence or non-crimed event type)
Victim **(Control)**	Sex
	Employment status
	Housing
	Mental health
	Physical health
	Alcohol/substance use
	History of violence
Perpetrator **(Control)**	Sex
	Employment status
	Housing
	Mental health
	Physical health
	Alcohol/substance use
	History of violence
Dyad **(Control)**	Relationship
	Dependents
	Living situation
	History of violence
Event **(Control)**	Offence type (crimed events)
	Non-crimed event type
	Event components (i.e. for events where multiple offences take place)

4.3. Curating a new police dataset

To build a new dataset, information was taken from the four data sources and manually recoded into a set of variables based on the measurement framework. This section of the chapter provides the methods for extracting and inputting data from the selected data sources to curate the dataset, including the sampling technique, test dataset, data input, and the method for deriving each of the variables. Four data sources were used: DA referrals, DASH, incident reports and crime reports. The referrals provided the base for creating the dataset. DA referrals should be submitted for all reported DVA events therefore should be available for all recorded events for each victim. DA referrals were available from the point the referral system was implemented in the force in 2002, to the point in which the referral system was replaced by a new system in the force in November 2018. Data from the referrals therefore captured the repetition for victims over more than a 15-year period, and enabled victims to be traced back through force systems. To build the dataset, a sample of DVA victims were identified and followed through force systems to identify all of their referrals.

4.3.1. Sampling technique

A random sample of crimes recorded with a DVA flag was taken from the crime dataset file using a random number generator. The sample was taken from the most recent quarter of the dataset, January – March 2018. Each crime in the dataset had an ILRN, which can be used to identify the event in other force systems. For each crime, the ILRN was searched in the force DA referral system. From the ILRN, the referral system identified the associated DA referral. If there was no associated referral, the crime was excluded from the sample. The referral provided the full name, DOB and address of the victim. The name and DOB for the victim was then searched through the DA referral system to load all referrals relating to the victim. In some cases, additional referrals were loaded for persons with similar names to the searched victim. Each referral was checked for additional details such as address, associated persons and notes made by police and partner agencies to ensure each extracted referral relates to the same person.

Each referral represented a new event. Each event was given a unique numeric identifier. To anonymise victims and perpetrators for the dataset, an ID index was created. Each new victim was allocated an identifier. Each referral names the perpetrator, and provides their DOB and address. Each new perpetrator was given an identifier. Identifiers were created using a random number generator in SPSS. Every victim and perpetrator was entered into the index with their name and ID. The index was stored securely on force systems. The anonymous ID numbers were entered into the curated dataset, no identifiable information was ever entered. An additional ID number variable was manually added to the dataset to identify unique dyads. For every matching victim and perpetrator combination, a unique number was added to the dataset. The ID number combined letters and numbers to both identify repeat pairs of individuals and to distinguish the role of each individual. Table 4.2 shows the structure of the dyad ID number.

Table 4.2 Structure of dyad ID number

Victim: Perpetrator	ID number
Person 1: Person 2	1a
Person 2: Person 1	1b

For each victim, every DA referral where they were named as either victim or perpetrator was entered into the curated dataset as a new event. Victims and events were entered into the dataset until a minimum threshold of 300 events was reached. A threshold of 300 was selected as it was a large enough sample size to facilitate statistical analysis though could also be completed within the time-limits of the study. As discussed in the Methodology chapter, the curation of the dataset was time-consuming. The researcher iteratively developed the variables to be included in the dataset and manually searched for, extracted and recoded information from across the four data sources into a new quantitative dataset. The process of taking information from these sources and inputting the detail into a quantitative dataset required searching for and identifying case files related to each victim, cross-checking case files to ensure they related to the same individuals, reading through case files to determine the available information, iteratively recoding information into categorical variables that aligned with the measurement framework, and manually inputting information into a new dataset. Due to the extensive and lengthy process required to curate the dataset, the aim was to build a sample large enough to facilitate statistical analysis whilst retaining time to analysis the data and complete the project within the required deadline. The process of curating the dataset started in June 2019 and reached 300 cases in December 2019.

It is not possible to specify the time taken to reach each 100 cases, as the process became quicker as the dataset developed and the variables were defined. The first cases took the longest to input, as the variables were iteratively developed as the number of cases increased and knowledge of the information within the data sources grew. Due to iterative development, there was a necessary process of backdating the dataset to add variables to the first inputted cases that were added later in the curation process.

The final curated dataset contains 325 events, relating to 68 victims and 94 perpetrators. The data covered a time-period of over 15 years, ranging from January 2003 – November 2018.

4.3.2. Test dataset

To determine whether data from the four sources could be recoded into a measurement framework, a test dataset was created. The aim of the test dataset was to identify the type of information that was collected across each source and to develop a set of variables and coding scheme for the curated dataset. The test dataset was opened as a Microsoft Excel spreadsheet. Preliminary variables were entered as blank cells into the dataset. The variables follow those named in Table 4.1 and were placed under the categories of victim, perpetrator, dyad, event, police action and police outcome.

A sample of 50 events were entered into the test dataset using the sampling technique. For each event, information that was deemed relevant to the variable was lifted directly from the four data sources as blocks of free-text. All identifiable information was manually redacted before the data were entered. This was repeated for the first 50 events. Whilst entering information into variable categories, a set of variables and a coding scheme were iteratively developed. The derivation of the required variables will be outlined in the following sections of this chapter. The full list of variables and coding scheme for the dataset is given in the Appendix.

4.3.3. Data input

The new dataset was opened as a blank SPSS dataset. The derived set of variables and coding scheme were entered into the dataset as blank variables, unless the variable was later computed within the dataset, such as the number of events per victim. The first 50 events were entered from the test dataset into the new dataset. The remaining events were entered directly into the dataset from the four data sources. For each new event, the DA referral was downloaded onto the force laptop. Information was then coded directly into the blank variables in the SPSS dataset on the researcher's personal laptop. Within the referral system, DASH was identified and loaded on the force laptop. Information from the DASH was then entered directly into the SPSS dataset.

The ILRN was then searched through the Command and Control system to locate the associated incident report. Information was coded directly from the incident report into the SPSS dataset. The incident report stated whether the event was crimed and provided a link to the crime report within the crime system. Information was coded directly from the crime report into the dataset.

4.3.4. Derivation of the required variables

The dataset had four units of measurement. The structure of the dataset facilitated the measurement of repeat DVA for victims over time, as all[5] events for each victim were extracted regardless of who the perpetrator was. As perpetrator information was available for each event, repeat DVA could also be measured for specific dyads over time. As perpetrators were not traced through information systems, not all events relating to them were extracted and thus repetition for perpetrators could only be measured within a dyad with a specific victim.

A set of variables and coding scheme were developed. As will been demonstrated in the Results Two data, many of the derived variables have missing data. In some cases, this is due to information not being recorded in standard fields where the information should have been recorded. In many cases, missing data is due to the variable being derived from the free-text which is not standardised and thus the information collected and extractable varies. In some cases, it is due to the information being derived largely from the DASH, and the DASH not being available for the case. In the curated dataset, 40% of DASH were not completed. Most of these (36%) were recorded as refused by the victim, the remaining 4% were deemed to have not been completed by the responding officer, based on available information in the free-text. Some of the variables affected include the recording of victim and perpetrator mental health, whether the dyad have any children and dependents, and measures of escalation such as 'Is the abuse happening more often?'. Where possible, information to populate these variables was taken from elsewhere across the data sources.

Five of the DASH questions are replicated in the dataset to measure severity. These are listed in section 4.3.4.5 as indicators of measures of event severity. These questions are included in the dataset as binary variables, and the binary indicator and free-text information in DASH are used to populate these variables. One other DASH question is replicated, and that is the question as to whether the victim has separated or tried to separate from the perpetrator in the last year. This question is included as previous research has associated separation with repeat DVA, as discussed in the Literature Review (Walby and Myhill, 2001; Almond et al, 2017). The remaining DASH questions were not included as individual variables in the dataset. This is partially due to the additional time that would be required to enter all 27 questions in the dataset when previous research indicates most risk assessment questions have no significant association with DVA repetition (McManus et al, 2017; Almond et al, 2017). All questions were also not included due to the large amounts of missing data that would be in these variables. Several of the DASH questions not stated here did contribute

[5] Excluding events for which no DA referral is submitted, or where the nominal has not been correctly attached to the individual.

towards the coding of the variables across the curated dataset, as is shown in the following subsections.

4.3.4.1. Victim and perpetrator variables

The required variables for the victim and perpetrator are the sex of the individual, the employment status, housing type, mental health, physical health, alcohol/substance misuse, and history of violence. Where a variable was recorded with a particular response (e.g. mental health issue, housing type), all subsequent events were recorded with that response, unless the circumstances of subsequent events indicated that the response had changed (e.g. changed employment status). Where no information was available in standard fields or free-text, the variables were recorded as unknown.

Sex

Male, female, other, unknown.

The sex of the victim and perpetrator were standard fields in the crime report. For non-crimed events, the sex of the victim and perpetrator were derived from gendered pronouns and terminology used in the free-text fields across the datasets. Gendered pronouns/terminology included terms such as ‘male’, ‘female’, ‘boyfriend’, ‘girlfriend’, ‘husband’, ‘wife’, ‘son’, ‘daughter’, ‘brother’ and ‘sister’. The force policy for defining sex and gender when recording events was unknown and may have changed over the time-period of the dataset. Sex was therefore defined in the curated dataset as police-identified sex.

Employment status

Employed, unemployed, economically inactive, unknown.

The occupation of the victim and perpetrator were standard fields in the DA referral. The occupation field was recoded to a categorical measure of whether the individual was employed, unemployed, or economically inactive. Students and retired persons were recorded as economically inactive.

Housing

Owner occupier, tenant – private or social, managed residential accommodation (e.g. student halls of residence), no fixed abode, living with family/friends, other (e.g. refuge, prison, hospital), unknown.

For a small number of events, information on the individual’s residence type was recorded in a standard field in the crime report, though this was not routinely completed. Information on the type of residence for the victim and perpetrator was largely derived from free-text narratives in the DA referral. As the information recorded in the free-text was not standardised, information on housing was inconsistent and often missing.

Mental health issues

Yes, no, unknown.

There was a standard field for recording victim/perpetrator mental health in the referral. Where the information was not recorded, information was derived from the free-text in the referral, DASH, and/or police warning markers. The selected police warning markers included 'mental health', 'self-harm', and 'suicidal'.

Mental health issues were recorded as present if the following DASH questions were recorded as 'yes':

'Are you feeling depressed or having suicidal thoughts?'

'Has (…..) had problems in the past year with drugs (prescription or other), alcohol or mental health leading to problems in leading a normal life? (Please specify what)'

'Has (…..) ever threatened or attempted suicide?' (Richards, 2009).

Physical health issues

Yes, no, unknown.

Physical health refers to any identified long-term physical health condition and/or disability. There was a standard field for recording victim/perpetrator physical health in the referral. Where the information was not recorded in the standard field, information was derived from the free-text fields across the data sources, and/or police warning markers in the referral or incident report. The selected police warning marker was 'ailment'.

Alcohol and substance misuse

Yes, no, unknown.

Alcohol and substance misuse were recoded as separate variables. Problems with alcohol/substance misuse were distinguished from whether the victim/perpetrator were intoxicated at the time of the event. Alcohol and drugs were standard fields in the referral where problems with alcohol and/or drugs were identified by officers.

For the victim, problems with alcohol use were derived from the free-text fields across data sources. A victim was recorded as having a problem with alcohol if they disclosed that they had a problem with alcohol; was an alcoholic; was alcohol dependent, or if the police identified that the victim had a problem with alcohol. Problems with substance misuse or drugs were derived from the free-text across data sources, and/or from the police warning marker 'Drugs'. A victim was recorded as having problems with substance misuse if the free-text states that they were using drugs, or were addicted to drugs.

For the perpetrator, problems with alcohol use were derived from the free-text fields across data sources, and/or from the DASH. A perpetrator was recorded as having a problem with alcohol if they or the victim disclosed a problem or dependency with alcohol, or if the police identified that the perpetrator had a problem with alcohol use. Problems with substance misuse or drugs were derived from the free-text across data sources, DASH, the police warning marker 'Drugs', and police intelligence, stated in the DA referral.

Alcohol and/or substance misuse problems were recorded as present if the following DASH questions were recorded as 'yes':

'Has (…..) had problems in the past year with drugs (prescription or other), alcohol or mental health leading to problems in leading a normal life? (Please specify what)' (Richards, 2009)

Identification through DASH relies on the victim disclosure of the perpetrator's problem with alcohol and/or substance misuse.

Whether the victim and/or perpetrator were intoxicated at the time of the event were standard fields in the crime report. For non-crimed events, and for crimes where the standard field was not recorded, information on whether the victim and/or perpetrator was intoxicated was derived from the free-text fields across data sources. Intoxication includes alcohol and other substances.

History of violence

Victims

Number of DVA events in the dataset (n)

For victims, history of violence refers to the victim's previous experiences of DVA. As all[5] DVA events for the victim were extracted into the curated dataset, victim history of violence was measured as the number of events naming the victim in the dataset.

Perpetrators

Number of convictions (n), previous convictions but number unknown, conviction history unknown due to no PNC check.

Offence types

Violence/sexual offences/criminal damage/other: yes, no, unknown.

Warning markers (violence, weapons)

Yes, no, unknown.

For perpetrators, history of violence was measured as the number of known previous convictions, and binary indicators of whether the perpetrator had convictions for specific offence types (violence, sexual offences, criminal damage, other). Information on conviction history was derived from the free-text of the referral.

For perpetrators, history of violence was also measured using police warning markers. Warning markers were recorded by MASH using PNC information. Warning markers were recorded as present when the DA referral stated the perpetrator has a warning marker(s) for violence and/or weapons.

4.3.4.2. Dyad variables

The required variables for the dyad are the relationship between the victim and perpetrator, whether the dyad have any children/dependents, whether the victim and perpetrator live together, and the history of violence.

Relationship

Partner/Ex, Son/Daughter, Brother/Sister, Parent, Grandparent, Other.

Intimate partner, family violence.

The relationship between victim and perpetrator was a standard field in the referral. The relationship variable was entered into the dataset using the same categories as the referral. An additional relationship variable was added that aggregated the relationships into IPV and FV.

Children/Dependents

Yes, no, unknown.

Children/dependents relating to the dyad were added to the DA referral as additional persons. Information was therefore derived from the free-text. Information on children/dependents between the dyad was also available in DASH. The variable was recorded as ‘yes’ if children/dependents were associated with both the victim and perpetrator i.e. a child from a previous partner that was not in the care of the dyad would not be recorded.

Dependents are recorded as present if the following DASH questions are recorded as ‘yes’:

Are there any children, step-children that aren't (…..) in the household? Or are there other dependants in the household (i.e. older relative)? (Richards, 2009).

Living situation

Yes - living with the perpetrator, No - was living with the perpetrator at the time of the event but is no longer, No - not living with the perpetrator, unknown.

Victim/perpetrator addresses were standard fields in the DA referral. These fields were used to derive whether the victim/perpetrator were living together or separately during the event. Information from the free-text was used to record whether the victim or perpetrator moved out of the shared property following the event, for instance whether the victim moved in with friends or family. In some events, the address fields stated that the victim and perpetrator reside at the same address though the free-text suggested they are living separately. Where there were discrepancies between the information in the standard fields and the free-text, the free-text overrode.

History of violence

Number of events in the dataset (n).

For dyads, history of violence refers to the number of previous reported DVA events. As all DVA events[5] were extracted for each victim, all reported DVA events relating to each dyad should be in the dataset. History of violence was therefore counted as the number of DVA events relating to the dyad in the dataset. The number of referrals between the dyad was often included in the free-text of the DA referral, though the number sometimes differed to the number of events recorded in the dataset. The number of events in the dataset overrode the free-text.

4.3.4.3. Event variables

The variables for the event include the offence type for crimed events, the event type for 'non-crimed' events, and the event components (i.e. types of events for events where multiple offences take place).

Crimed event type

Home Office crime category.

When a reported event crosses the criminal threshold and is recorded as a crime by the police (Home Office, 2020a), the offence is given a Home Office offence type, offence code and offence category. For instance, Common Assault and Battery is an offence type, the offence code is 105/1, and the offence category is Assault without Injury. The offence type summarises the event and prompts specific criminal justice responses. Where multiple offences have taken place in the same reported event, only one crime is recorded, usually the most serious offence. The exception to this is events where the offence contributes to a course of conduct crime (e.g. Controlling or Coercive Behaviour, Stalking/Harassment), then both crimes are recorded (Home Office, 2020a). The offence type, code and category were standard fields in the crime report. The variable was derived from the standard field. For some events, only the offence category and code were recorded by police and there was no given offence type. For events where two crimes were recorded, each crime was entered as a separate case into the dataset.

'Non-crimed' event type

Crimed event, verbal altercation, breach, threats, stalking, harassment, theft, criminal damage, assault without injury, assault with injury, rape, other sexual offences, other.

To describe the circumstances of crimes, crimed events have a Home Office crime category. The only equivalent code for incidents, or 'non-crimed' events, is an incident code. As stated in the description of incident report, the DVA incident codes are 'Domestic Incident' and 'Domestic Crime' which provide no information on the circumstances of the event.

To describe the nature of events that were not crimed, a new variable was curated. The new variable provided a list of summary codes to describe the event. One code was given to each event. Some of the codes paralleled offence categories e.g. criminal damage, assault with injury and assault without injury. Other codes described circumstances that did not correspond to any specific offence categories e.g. verbal altercation, threats. All codes were derived from the free-text fields across all data sources. A code that paralleled an offence category was given if the free-text uses the terminology of the category e.g. if the free-text stated harass, harassment, harassed, harassing etc. then the event may have been coded as harassment. A code that paralleled an offence category may also have been given if the text describes circumstances that could amount to an offence type e.g. if the perpetrator took the property of the victim which led to a dispute, this may be coded as theft. The 'non-crimed' event code variable allowed the circumstances of all events to be considered in the analysis regardless of whether the event was recorded as a crime. Non-crimed events that were given a code that parallels an offence category were based on the researcher's interpretation of the available information. It is possible that these events involved criminal offences that were non-crimed, or that the circumstances of the event did not amount to a notifiable offence, or that the police had credible evidence to suggest that an offence did not take place. This information was not available.

Event components

Individual variables: verbal, breach, threats, stalking, harassment, theft, criminal damage, assault without injury, assault with injury, rape, other sexual offences, other.

When multiple offences occur in the same event, only one is recorded (excluding course of conduct crimes). This means that any additional offences are not captured in the data, and information on the types of DVA events that come to police attention is lost. To capture all offences or components that characterise an event, 12 new variables were added to the dataset. Each variable was a binary yes/no measure of whether a particular offence or event type took place. The 12 variables disaggregated the non-crimed event variable. Each event may have had up to 12 of the event component variables present. The variables provided more description of what happened in each event than the summary codes. For crimed events, one component could be derived from the standard Home Office crime category field in the crime report. All other components were derived from free-text fields across all data sources.

4.3.4.4. Police action variables

The available police action variables are the response grading, risk assessment, arrest, referral to other agencies, referral to MARAC, charge of the perpetrator, police disposal.

Response grading

Emergency, priority, planned, telephone, police report.

The response grading stated whether frontline officers attended the event, and how quickly they attended. The grading was a standard field in the incident report.

Risk assessment

Standard, Medium, High

Risk classification was a standard field in the DASH and DA referral. The variable was taken from these fields. DASH was introduced to the force in March 2009. The risk classification was therefore not available for events recorded prior to March 2009. For all events prior to the 1st April 2009, the variable was recorded as missing.

Arrest

Yes, no, unknown.

The number of persons arrested was a standard field in the incident report and DA referral. The free-text in the report and the referral indicated who was arrested. Information was taken from standard fields and from the free-text to record whether the perpetrator was arrested.

Referral to other agencies

Yes, no, unknown

Individual variables: probation, IDVA, health, mental health, CSC, CFW, ASC, education, substance misuse, other.

Whether the referral was referred to any other agency was a standard field within the referral system, though not a standard field in the referral. In the DA referral, there was a standard field for the referral decision. The referral decision included whether the event was referred to IDVA or CSC, though did not include any other agencies. Information on whether the referral was referred to another agency was taken from standard fields in the referral for some events, though for most events the information was manually derived from the free-text fields in the referral or taken directly from the referral system. There was one variable in the dataset to determine whether the referral was shared with any agency. There were 10 individual variables to record whether the referral was shared with each agency. The force stated that IDVAs were introduced to the force area in 2007. All events recorded prior to 1st January 2008 were therefore recorded as missing for the referral to IDVA variable. All other agency variables were available throughout.

Referral to MARAC

Yes, no, unknown.

Referral to MARAC was a standard field in the DA referral. The variable was derived from the standard field. The force stated that MARACs were introduced to the force area in 2007. All events recorded prior to 1st January 2008 were recorded as missing.

Police disposal

<u>Crime status</u>: Undetected, positive outcome, cancelled, positive outcome restorative justice, prosecution not possible, closed, crime under active investigation, court disposal, police disposal, no further action (NFA).

<u>Crime outcome</u>: variable with 30 responses including charge/summons, adult caution, community resolution, and case closed (see Appendix).

The police recorded crime status and crime outcome were standard fields in the crime report. The crime status field captures whether the crime resulted in a disposal or NFA. The crime outcome field provides more information on the type of police disposal and reasons for a case resulting in a close or NFA. Both were entered directly into the curated dataset as new variables with all available status' and outcomes as the coding scheme. To focus on the impact of certain outcomes, such as charge or NFA, the variable was aggregated into new binary variables (e.g. charge/no charge).

Police disposals that are specific to DVA events such as DVPOs/DVPNs and non-molestation orders were not recorded across any of the included data sources and therefore not included in the dataset. There was no information in the data sources on types of court disposals, these were therefore not included in the dataset. More data sources could be required to extract information on specific police disposals.

4.3.4.5. Repetition variables

Measures of frequency and severity were derived from the data and produced in the dataset. The method of defining frequency and severity for the dataset is given in Methods chapter, and summarised here.

Frequency

Frequency was measured as the number of DVA events per victim/dyad, and as the change in frequency over time. The number of events per victim/dyad was calculated within the dataset. The change in frequency was measured through latent trajectory analysis.

Severity

Severity was measured as the severity of each individual event, and as the change in severity over time. Several measures were added for the severity of each event. The change in severity over time is measured using derived variables in the dataset, and through latent trajectory analysis. For each event, severity was measured as whether the event was crimed, violent (with and without injury), and by severity score. Each were added as new variables to the dataset.

<u>Crimed</u>

Yes, no.

Standard field in the incident report and in the DA referral. The information was taken from the standard fields.

<u>Violent</u>

Non-violence, violence without injury, violence with injury.

Whether the event involved violence (with and without injury) was taken from the event components variable. The events component variable was derived from Home Office offence types and categories, and from free-text information across data sources.

Severity scores

Three severity scales were considered for measuring the severity of each event (see Methodology). Each severity scale allocated a numeric score to an event based on the offence type. Each scale was adapted to the data. Each score was derived from the offence codes and the non-crimed event type variables.

Change in severity

Yes, no, unknown.

Change in severity was measured using derived variables in the dataset, and through latent trajectory analysis. The derived variables in the dataset measured whether the DVA was getting worse from the victim's perspective, derived from DASH. Each was a binary variable coding yes/no to the following questions.

Is the abuse happening more often?

Is the abuse getting worse?

Has the perpetrator ever used weapons or objects to hurt the victim?

Has the perpetrator ever threatened to kill the victim or someone else?

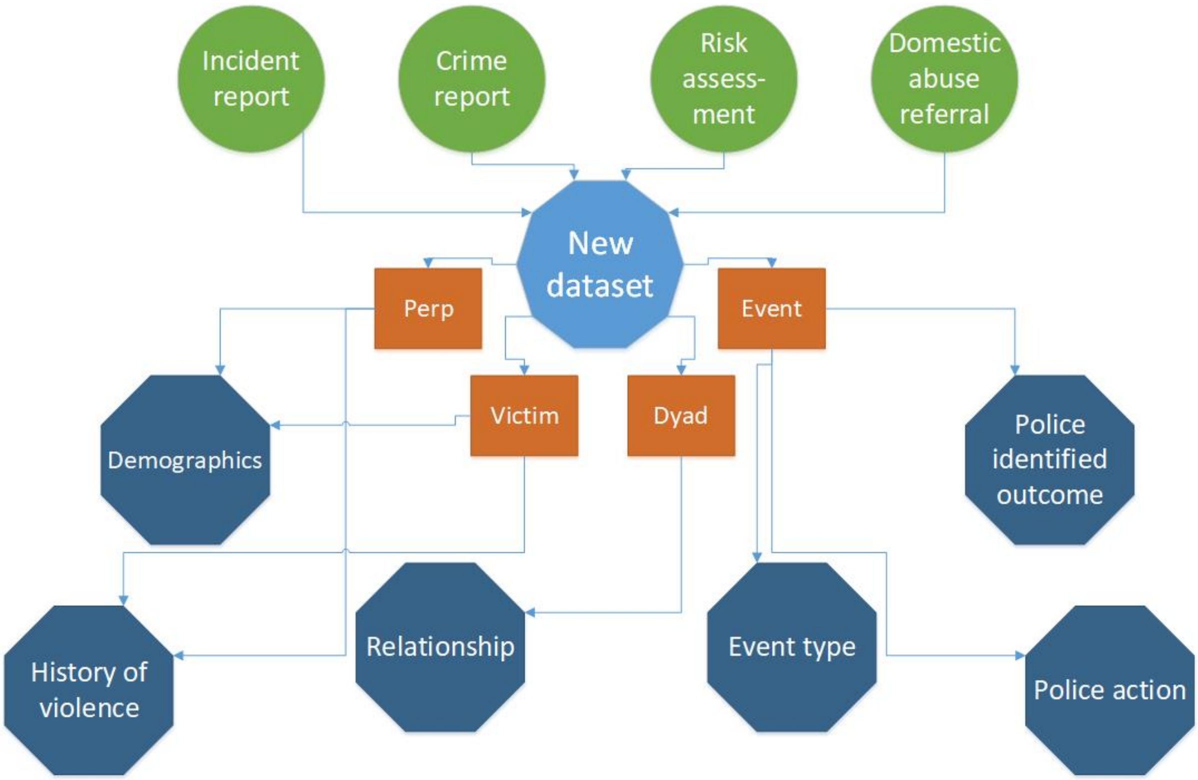
Has the perpetrator ever attempted to strangle/choke/suffocate/drown the victim? (Richards, 2009)

Additional information was taken from the free-text fields. A comparison of the presence of the derived measures in the first event and the last event for repeat dyads gave an indication of escalation in the severity of reported DVA over time.

4.4. Comparison of curated dataset and existing police datasets

The curated dataset combined all the required variables and units of measurement in the measurement framework (Table 4.1) for measuring DVA repetition and assessing the effect of police action. Information was manually derived from four data sources into numeric and categorical variables and structured into a format that enabled statistical analysis. Figure 4.1 summarises the restructure, showing the data sources, units of measurement and the new categories of available information. This section considers why the curated dataset was better suited to measuring patterns of DVA repetition and police data than the original police datasets.

Figure 4.1 Restructure of police data sources into a new quantitative dataset



In the existing datasets, standard fields enable large amounts of data to be quickly extracted from information systems into quantitative datasets. However, as discussed, the existing datasets were not suitable for measuring DVA repetition. This was because the structure of existing police data prevented the identification of repetition across systems, and essential information was lost in free-text and not routinely collected in standard fields. The curated dataset addressed some of the key issues.

Firstly, existing police datasets could not accurately measure repetition across datasets due to each containing different units of measurement, and the inconsistent recording of personal details that identified units of measurement. This meant that when the multiple police datasets were merged, repeat persons could not be identified. The curated dataset combined information on victims, perpetrators and events, thus each unit of measurement was included and datasets did not need to be merged. Each victim/perpetrator were given unique numeric identifiers, which were resistant to changes in name or address. The identifier enabled the measurement of repetition.

Further issues in existing police datasets included the misapplication of DVA flags and the multiple methods of identifying DVA. The misapplication of DVA flags for events that did not meet the definition of DVA may have produced multiple singular events in the data that contributed towards an underestimate of the extent of repetition. Furthermore, the use of multiple flags produced multiple overlapping though different DVA samples, and each could have a different repetition estimate.

The curated dataset used one police definition of DVA, the DA referral. The referral had the clearest definition of DVA across all police data sources. DA referrals should be submitted for all DVA events. The purpose of the referral was to share information on the victim, perpetrator and event with MASH to facilitate safeguarding and prevent further DVA. The referral was identified as DVA using one 'DA' code. Events only had a DA referral when both victim and perpetrator were identified, both were real people, both were domestically related and the police identified that the event was DVA. Each event added to the dataset had an associated referral. Unlike crime data, referrals did not include events where there was no victim, or where the victim was not a domestic relation of the perpetrator. Unlike incident data, there was only one code to define the referral as DVA. The curated dataset was therefore unaffected by the use of different codes and flags in the incident and crime reports. All events in the curated dataset should reflect the definition of DVA due to the event criteria for a DA referral to be submitted. However, it is possible that not all DVA events reported to the police resulted in a DA referral, and thus referrals were still an underestimate of DVA repetition, though provided the best measure available of all police data sources.

Furthermore, though the police collect lots of data, many of the required variables on police/agency action and the personal/situational factors of victims/perpetrators were not recorded as standard fields and were found within free-text narratives that were not directly extractable as quantitative variables. The curated dataset manually recoded the information provided in the free-text into a set of quantitative variables. The curated dataset thus enabled this information already collected by the police to contribute towards statistical analysis of DVA repetition.

Finally, the curated dataset derived variables of both frequency and severity to measure repetition. In existing datasets, the main measure of severity that can be used is the offence code, which is available for crimed events. The offence code gives the type of crime, including whether the event is classified as violence and whether the event resulted in injury to the victim. There is no measure of severity available in existing police datasets for non-crimed events. The curated dataset provided a new method of measuring severity for non-crimed DVA events with a non-crimed event type variable. The curated dataset therefore provided a better measure of severity than existing police datasets and was able to assess escalation in DVA over time. For the frequency DVA, the curated dataset captured more DVA than existing police datasets. Descriptive analysis of the crime dataset found that between 2015-18, 21% of victims had two or more recorded and flagged DVA crimes recorded by the force. In the same time-period, the curated dataset found that 51% of victims have two or more DVA events (crimed and non-crimed) recorded by the force. Some of this difference is accounted for by the inclusion of non-crimed events. A more comparable figure could be the percentage of repeat incidents in the incident data, though the incident data lacked a unit of measurement for victims thus repetition could not be identified. The estimate of repetition may have also been improved by the use of DA referrals as a base measure of the number of DVA events, rather than the number of incidents which relies on the selection of a particular incident code or flag to identify DVA events.

The dataset demonstrated that police data can be restructured into a format that enables the measurement of repeat DVA and thus facilitates analysis on the nature of DVA and the effectiveness of police interventions. The curation of the dataset thus establishes a new methodology for deriving information on DVA and police action. Furthermore, if police forces revised their systems of collecting and storing the information that they already collect, these data could be readily available for use by both police and researchers. A set of criteria for future police data collection was derived, shown in Table 4.3. The implications of these criteria for future police data collection and a new methodology for restructuring existing police data are considered in the Discussion chapter.

Table 4.3 Criteria for future police data collection on DVA

Criteria for police data collection on DVA
Table 4.1 provides a measurement framework for measuring repeat DVA and evaluating police action. These variables should be collected consistently and accurately by police forces.
To ensure repetition is captured, data need to include units of measurement on the event, victim and perpetrator.
Data on DVA events, victims and perpetrators should be stored within one information system, to reduce the time required to locate and extract multiple data sources.
If data are recorded across multiple systems, each should attach the individual ID number to allow multiple datasets to be merged and repeat individuals to be matched.
To ensure the matching of repeat individuals, each individual should be allocated a unique ID number. The ID number should be resistant to changes in personal details, for instance comprised of random numbers and letters rather than derived from personal details.
DVA flags should identify events as DVA rather than incident codes. Incident codes should describe the event e.g. breach, threats, verbal altercation.
One DVA flag should be attached to all events of DVA. The flag should be attached to events that fit the definition of DVA (Home Office, 2020a).

4.5. Conclusion

This chapter presented a measurement framework for measuring DVA repetition and police action, and the method of reconstructing existing police data into a quantitative dataset that enables statistical analysis. This framework and dataset are presented in a Results chapter as they contribute two of the key outputs of the thesis, and contribute to addressing the third research question for the thesis:

How can police data be improved to measure DVA repetition?

The Methodology chapter identified and reviewed the available data. This Results chapter has provided a framework for reconstructing police data into a format that enables the statistical analysis of DVA repetition and police action. The following Results Two chapter provides the results of the statistical analysis, that serves to demonstrate the potential of police data to measure patterns of DVA repetition and investigate any impact of police action on DVA repetition.

5. Results Two: Statistical Analysis of Domestic Violence and Abuse and Police Action

5.1. Introduction

Though the thesis is focused on measurement, embedded within this focus are the implications for police practice and research of an improved police measurement system that enables analysis and understanding of DVA repetition and the impact of police actions. The previous chapter presented the measurement framework and procedure that curated a new dataset, reconstructing multiple sources of police data into a quantitative form for analysis. The resulting measurement framework and curated dataset are key outputs of the thesis. To test the ability of police data to measure DVA repetition and police action, a series of statistical analyses were conducted on the curated dataset. Due to the extensive process of curating the dataset, as detailed in the previous chapter, the dataset has a relatively small sample of 325 DVA events, relating to 68 victims and 94 perpetrators. The results of the analyses are therefore not interpreted to be representative of all DVA. The results are interpreted as relevant to the specific sample of DVA contained within the dataset, and as a demonstration of the potential of police data when reconstructed using the measurement framework proposed by the thesis (Table 4.1).

To structure the analyses, two subsets of research questions were derived, based on DVA repetition and police action.

Patterns of DVA repetition

- Are victims female and perpetrators male?
- Does DVA escalate in frequency and severity?
- Do DVA trajectories compare with typologies identified in the literature?

Relationships between police actions and DVA repetition

- What action do the police take in response to DVA?
- Is there any association between the type of police action taken and the frequency of DVA?
- Is there any association between the type of police action taken and the severity of DVA?

This Results Two chapter starts with an overview of the dataset, looking at the characteristics of victims, perpetrators and events. The remaining sections are then structured around the two sets of analysis research questions. The findings are discussed in relation to the research questions in the subsequent Discussion chapter.

5.2. What is the nature of domestic violence and abuse that is recorded by police?

The nature of DVA refers to the characteristics and patterns of DVA events, victims, perpetrators, dyads. As discussed in the Literature Review, competing theories contest the nature of DVA. This section will present the results of analyses into some of these debates, including the extent to which the DVA in the dataset was gendered and escalatory. The characteristics of the curated dataset are then compared to the characteristics of key debates in the literature. The findings are considered in greater depth in the Discussion chapter.

5.2.1. Characteristics of domestic violence and abuse

Descriptive analyses were conducted in SPSS to summarise the characteristics of the victims, perpetrators, dyads, and events.

5.2.1.1. Victims

Age

Repeat victims that appear in the dataset for more than one year changed in age throughout the dataset. The mean difference in the first and last age for victims is three years. The largest difference between the first and last age for a victim was 15 years. In order to compute the mean age of victims in the dataset, first the mean age of each victim was computed, then the mean age for all victims was computed (shown in Table 5.1). The mean age of victims in the dataset was 33 years. This was repeated for the median age. The median age was 31 years.

Table 5.1 Average age of victims

	Minimum	Mean	Median	Maximum
Age in years	16	33	31	63

Ethnicity

The disaggregated categories of ethnic group have been suppressed into ‘White’ and ‘Other’ due to the small numbers of victims in the disaggregated categories. Table 5.2 shows the majority (97%) of victims were classified as ‘White’.

According to the 2011 census, 90% of the county in which the force operate were of white ethnic background, the black and minority ethnic group accounted for 10% of the population. The underrepresentation of ethnic minority victims in the dataset does not suggest that ethnic minority communities experience less DVA but that the DVA experienced by these communities has not been captured in this dataset. As discussed in the Literature Review, research has suggested there is no significant difference in DVA victimisation by ethnic group (Walby and Allen, 2004), underrepresentation of ethnic minority victims in DVA populations may relate to the additional challenges faced by victims from ethnic minority communities to seek police and agency support (Barnish, 2004).

Table 5.2 Ethnicity of victims

Ethnicity	Percentage of victims (%)
White	97
Other[a]	3

[a]Number of victims is too small to provide disaggregated ethnicity figures

Data were missing for 1% of victims, these cases were excluded

Employment status

Table 5.3 shows the employment status of victims changed for some repeat victims recorded throughout the dataset. Frequency tables of victim employment status were computed for the first and last recorded event for each victim. For victims with one event (46%), the first and last refers to the same event. More than half of victims (64%) were recorded as unemployed in their first DVA event. Less than a third (32%) were recorded as employed at the time of their first recorded DVA event with the force.

The most recent ONS (2020b) figures for England and Wales estimated the UK unemployment rate to be 3.9% between April and June 2020, significantly lower than the estimate for the victim population of the dataset. This may reflect the literature that states DVA victimisation is concentrated against victims of lower economic status (Walby and Towers, 2018).

Table 5.3 Victim employment status

Employment status	First event: percentage of victims (%)	Last event: percentage of victims (%)
Unemployed	64	61
Employed	32	36
Economically inactive	4	4

Data were missing for 18% of victims, these victims were excluded from the count

Housing

The type of housing a victim resides in changed for some victims throughout the dataset. Frequency tables of housing type were computed for the first and last event for each victim. For victims with one event, the first and last refer to the same event. Where the first event for a victim was recorded was unknown, the first event with a known outcome was taken. As the recording of housing type was not standardised, information was missing for over half of victims (62%). Missing cases were not included in the count. The figures in Table 5.4 represent the percentage of victims for which information on housing type was recorded that were coded with each housing type in the curated dataset. Some types of housing may be more likely to be recorded by the police if the victim's housing type was deemed important to the referral for safeguarding, such as if the victim was of no fixed abode. These housing types could be overrepresented in the available data.

The most common housing types for victims in the first event was a tenancy of any kind, or to be living with family or friends (both 39%). The percentage of victims owning their own home decreased from 12% for victims in their first recorded DVA event to 8% of victims in their last recorded event. The percentage of victims holding a tenancy increased from 39% for victims in their first recorded event to 46% for victims in their last recorded event. The percentage of victims recorded as having no fixed abode increased from 4% for victims in their first recorded DVA event, to 12% for victims in their last recorded DVA event.

In 2020, the Ministry of Housing, Communities and Local Government (MHCLG) reported that 63% of households in England owned their own homes in the 2 years from 2016 to 2018. This is much higher than the 12% of victims estimated in the dataset to have owned their own home. Housing is one indicator of economic inequality, with home ownership an indicator of higher economic status (Walby and Towers, 2018). The low proportion of victims owning their own home in the curated dataset may therefore reflect the literature that individuals of lower economic status are overrepresented in DVA victims. Walby and Towers (2018) in their analysis of CSEW data found a split of between 32-35% of DVA victims owning their home compared to 66% of the general population, with between 65-68% of DVA victims living in rented accommodation compared to 34% of the general population. The results from the dataset show a similar pattern in that the percentage of DVA victims living in rented accommodation is much larger than the percentage that own their own homes, but both percentages are lower than those found in Walby and Towers' victim population. This is due to the inclusion of alternative living status' in police data, for instance living with parents/family/friends, which is one of the highest percentages in the curated dataset, with 39% of victims residing with others in their first recorded events, managed residences such as student accommodation, emergency or institutional residence such as refuges or prison, and temporary accommodation (such as homeless shelters) or no fixed abode. These forms of residence are not included in the CSEW, thus victims residing in these alternative residences, which account for half of those recorded in the curated dataset, are not captured in CSEW victim populations.

Table 5.4 Victim housing

Housing type	First event: percentage of victims (%)	Last event: percentage of victims (%)
Owner occupier	12	8
Tenant (private, social, other)	39	46
Other managed residence (e.g. student halls, hospital staff accommodation)	4	4
No fixed abode/homeless/temporary accommodation	4	12
Living with parents/family/friends	39	27
Other (e.g. refuge, hospital, prison)	4	4

Data were missing for 62% of victims, these cases were excluded

Individual factors

The individual factors included in the curated dataset include physical illness or disability, mental health issues, problems with alcohol use, substance misuse and financial issues. Each factor was a binary variable that coded whether the victim was identified as having the factor present in at least one event. For repeat victims, if the factor was identified in one event, the factor was recorded for all subsequent events. Both victims where the factor was recorded as not present and victims where the information was unknown were counted as not having the factor identified, unknowns are therefore included in the count. Table 5.5 shows that 10% of victims were identified as having a physical illness/disability, more than a third as having mental health issue(s) (37%), 16% as having problems with alcohol use[6], 16% with substance misuse[6], and more than a quarter (28%) were identified as having some form of financial issues in at least one recorded event.

[6] Problems with alcohol and/or substance misuse are defined and recorded separately to variables that measure whether the individual was intoxicated at the time of the event

The proportion of victims experiencing mental health problems, alcohol and/or substance abuse problems is higher than the percentage of the wider population. An estimated 17% of adults in England and Wales have problems with their mental health (McManus et al, 2016). Regarding alcohol/substance use, 16.6% of adults are estimated to consume hazardous levels of alcohol, 1.9% to have harmful or mildly dependent drinking and 1.2% to have probable dependency, whilst 3.1% are estimated to have a drug dependency (McManus et al, 2016). The characteristics of the sample could suggest that these factors are much more prevalent in the victims that come to police attention. Mental health issues, alcohol/substance misuse have been associated with DVA victimisation in the literature (Walby and Myhill, 2001; Schumcher and Holt, 2012), though it is difficult to distinguish cause and consequence of these individual factors and DVA.

Table 5.5 Percentage of victims with identified health, substance use or financial issues

Individual factor	**Percentage of victims (%)**
Physical illness or disability	10
Mental health issue(s)	37
Problems with alcohol use	16
Problems with substance misuse	16
Financial issues	28

5.2.1.2. Perpetrators

Age

Repeat perpetrators that appear in the dataset for more than one year, changed in age throughout the dataset. The mean difference in the first and last age for perpetrators was two years. The largest difference between the first and last age for a perpetrator was 15 years. In order to compute the mean age of perpetrators in the dataset, first the mean age of each perpetrator was computed, then the mean age for all perpetrators was computed (shown in Table 5.6). The mean age of perpetrators in the dataset was 33 years. This was repeated for the median age of perpetrators. The median age of perpetrators was 32 years.

Table 5.6 Average age of perpetrators

	Minimum	**Mean**	**Median**	**Maximum**
Age in years	16	33	32	66

Ethnicity

The disaggregated categories of ethnic group were suppressed into 'White' and 'Other' due to the small numbers of perpetrators in the disaggregated categories. The majority of perpetrators (98%) were classified as 'White'. As discussed earlier, this percentage is differs to that of the wider population of the force area, in which 90% are of white ethnic background. DVA within ethnic minority communities may be underrepresented in the sample.

Table 5.7 Ethnicity of perpetrators

Ethnicity	Percentage of perpetrators (%)
White	98
Other[a]	2

[a]Number of perpetrators is too small to provide disaggregated ethnicity figures

Data were missing for 1% of perpetrators, these cases were excluded

Employment status

Frequency tables of perpetrator employment status were computed for the first and last event for each perpetrator. The percentages in the table represent the percentage of perpetrators for which information on their occupation was recorded in police data that were coded as employed, unemployed or economically inactive in the curated dataset. For perpetrators with one event (48%), the first and last refer to the same event. Table 5.8 shows more than two thirds (68%) of perpetrators were recorded as unemployed in their first DVA event.

The proportion of unemployed perpetrators in the sample is higher than the percentage for the wider population, which is 3.9% (ONS, 2020). The dataset population may support previous research which has found associations between unemployment or intermittent employment and the perpetration of DVA (Kyriacou et al, 2011; Barnish, 2004).

Table 5.8 Perpetrator employment status

Employment status	First incident: percentage of perpetrators (%)	Last incident: percentage of perpetrators (%)
Unemployed	68	63
Employed	28	33
Economically inactive	4	4

Data are missing for 20% of perpetrators, these cases were excluded

Housing

Frequency tables of housing type were computed for the first and last event. For perpetrators with one event, the first and last are the same event. Where the first event for a perpetrator was unknown, the first event with a known outcome was taken. As the recording of housing is not standardised, it was missing for over half of perpetrators (60%). Missing cases were not included in the count.

Table 5.9 shows the most common housing type for perpetrators in their first DVA event was living with family or friends (42%). The second most common type was a tenancy of any kind (34%). The percentage of perpetrators recorded as no fixed abode increased from 11% for perpetrators in their first DVA event to 16% for perpetrators in their last DVA event.

As stated earlier, housing is an indicator of economic inequality (Walby and Towers, 2018). The low percentage of DVA perpetrators in the sample that owned their own home may indicate that most perpetrators in the dataset were of a lower socioeconomic status.

Table 5.9 Perpetrator housing

Housing type	**First event: percentage of perpetrators (%)**	**Last event: percentage of perpetrators (%)**
Owner occupier	8	5
Tenant (private, social, other)	34	34
Other managed residence (e.g. student halls, hospital staff accommodation)	3	3
No fixed abode/homeless/temporary accommodation	11	16
Living with parents/family/friends	42	40
Other (e.g. refuge, hospital, prison)	3	3

Data are missing for 60% of perpetrators, these cases are excluded

Individual factors

Each individual factor variable was binary and coded whether the perpetrator was recorded with a factor in at least one event. Both perpetrators where the factor was recorded as not present and perpetrators where the information was not given (unknown) were counted as not having the factor identified, unknowns were therefore included in the count. Table 5.10 shows that 3% of perpetrators were identified as having a physical illness or disability in at least one event, more than a quarter (30%) with mental health issues, 32% with problems with alcohol use[6], 33% with substance misuse[6], and 20% as having financial issues.

The proportions of perpetrators experiencing mental health issues, problems with alcohol use and/or substance use is higher in the dataset than in the wider population (see McManus et al, 2016). These differences are supported by previous research. Specific mental health issues, in particular depression (Riggs et al, 2000; Barnish, 2004), have been associated with DVA perpetrators. Alcohol and substance abuse have been identified as risk factors to DVA perpetration or as higher amongst DVA perpetrators than in the general population (Kyriacou et al, 1999; Riggs et al, 2000; Abramsky et al, 2011).

Table 5.10 Percentage of perpetrators with identified health, substance use or financial issues

Individual factor	**Percentage of perpetrators (%)**
Physical illness or disability	3
Mental health issue(s)	30
Problems with alcohol use	32
Problems with substance misuse	33
Financial issues	20

Perpetrator offending history

Warning markers and previous convictions were produced for the first event relating to the perpetrator where the information is recorded. Table 5.11 shows one-fifth (20%) of perpetrators had a known warning marker for violence and/or weapons. 43% of perpetrators had no warning marker. Warning markers were unknown for 37% of perpetrators.

Table 5.11 Percentage of perpetrators with a known warning marker for violence and/or weapons

	Percentage of perpetrators (%)
Warning markers for violence or weapons	20

Data were unknown for 37% of perpetrators, unknown cases were included

Table 5.12 shows that 45% of perpetrators had known previous convictions. 16% did not have previous convictions, and data were missing for 39% of perpetrators. Data were missing when no PNC check was conducted on any of the events relating to the perpetrator. Over one third (34%) of perpetrators were recorded as having known previous convictions for violence. No previous violence convictions were recorded for 27% of perpetrators. Conviction history for violence was unknown for 39% of perpetrators. Unknown cases were included in the denominator when calculating the percentage of cases with known convictions as the focus is on the percentage of perpetrators that were identified as having previous convictions, rather than a comparison of categories. The percentage of missing data varies by type of offence. This is because the recording of conviction data from PNC to DA referral was non-standardised. In some referrals, all known convictions were recorded, therefore all offence types were known. In some referrals, convictions were written into the free-text. For instance, in one referral, the free-text stated the perpetrator has previous convictions for violence and damage that led to a restraining order to protect the victim. Other conviction types were not recorded in this referral, therefore sexual offences and other offence types were recorded as unknown. In some referrals, only 'relevant' convictions were listed in the referral i.e. convictions relating to violence, sexual offences and criminal damage. For these referrals, other types of offences were recorded as unknown.

For sexual offences, 4% of perpetrators had known previous convictions, 54% had no convictions and 42% were missing. For criminal damage, 17% of perpetrators had with known previous convictions, 44% had no previous convictions and 39% were missing data. For other types of offences, 38% were recorded with previous convictions, 20% with no convictions and 42% were missing data. It is expected that these percentages could be higher if data were available for all perpetrators. Previous research has found that DVA perpetrators are more likely than non-perpetrators to have had contact with the CJS (Barnish, 2004) and previous violence in particular has been identified as a risk factor for DVA perpetration (Abramsky et al, 2011).

Table 5.12 Percentage of perpetrators with known previous convictions

Previous convictions	Percentage of perpetrators (%)
Any previous convictions[a]	45
Offence type	
Violence[a]	34
Sexual offences[b]	4
Criminal damage[a]	17
Other[b]	38

[a]Data were unknown for 39% of perpetrators, these cases were included

[b]Data were unknown for 42% of perpetrators, these cases were included

5.2.1.3. Dyads

Relationship

Table 5.13 shows more than three quarters (77%) of dyads were intimate partners or ex-intimate partners, 23% of dyads were family relations. Within FV, brother/sister was the most common, accounting for 12% of all dyads. Literature debating the nature of DVA has often separated and analysed IPV (Dobash and Dobash, 2004; Stark, 2007; Johnson, 2008) and FV (Straus, 1979) as separate phenomena. The separation of research into IPV and FV implies that the two phenomena are of different causes and consequences. This thesis follows the argument that DVA is caused by inequalities, in particular gender and economic inequalities, which affect both intimate partner and family relations. Therefore, IPV and FV are measured as one phenomena that is DVA between intimate and family relationships and are only separated to examine specific relationship characteristics, such as relationship type and separation for intimate partners.

Table 5.13 Dyad relationship

Relationship	Percentage of dyads (%)
Partner/Ex	77
Brother/Sister	12
Son/Daughter	4
Parent	7
Grandparent	<1

For intimate partners, frequency tables gave the percentage of dyads that were separated in their first and last DVA event. Non-intimate partners were treated as missing. Table 5.14 shows in the first event, almost half of intimate partner dyads (47%) were still together when the event was recorded. The percentage of dyads still together decreased to just over a third (37%) by the last recorded event. In the first recorded DVA event, one fifth of dyads were together at the time of the event though had separated or tried to separate at some point within the last year, this decreased to 17% by the last event. For the last event recorded per dyad, the largest category for intimate partner dyads was separated (45%), followed by not separated (37%).

It is possible that the dyads split and got back together multiple times throughout the recorded DVA series, the fluctuation in relationship status was not examined beyond the first and last event. When a victim is trying to leave a perpetrator, the dyad may split and recouple multiple times, as shown by the percentage of dyads that tried to split or had split and gotten back together within the last 12 months. Previous research has found separation from an intimate partner to be high-risk factor for DVA (Kyriacou et al 1999; Walby and Myhill, 2001), thus separation should be recognised by the police as a heightened risk period for further and more serious violence (Walby and Myhill, 2001).

Table 5.14 Relationship status of intimate partner dyads

Relationship status	First event: percentage of dyads (%)	Last event: percentage of dyads (%)
Not separated	47	37
Tried to separate or have separated at some point within the past year	20	17
Separated	34	45

For both intimate partner and family dyads, frequency tables gave the percentage of dyads that were living together in their first and last recorded event. Table 5.15 shows the largest category was that the dyad were not living together at the time of the event, accounting for 62% in the first event and increasing to 69% in the last event. The percentage of dyads living together decreased from 30% in their first recorded DVA event to 25% in their last recorded DVA event. For dyads with one event, the first and last event are the same event.

Table 5.15 Percentage of victims living with the perpetrator

Living with the perpetrator	First event: percentage of dyads (%)	Last event: percentage of dyads (%)
No – not living with the perpetrator	62	69
No – was living with perpetrator but has left, or perpetrator has left, since the current event	7	6
Yes	30	25

Data were missing for 3% of dyads, these cases were excluded

5.2.1.4. Events

The section starts with a description of all events in the dataset, looking at the presence of violence and event types. The section then looks at the offence types in crimed events, followed by the event types of non-crimed events. The section then presents some of the circumstances surrounding events e.g. location.

Violence and non-violence

Violence is defined as physical violence, including sexual violence. Non-violence refers to all other non-physical forms of abuse captured in the data. Frequency tables gave the percentage of all events (crimed and non-crimed) that involved physical violence. For events that have a non-violent crime code such as theft but also involved violence, the event was recorded as violent. Table 5.16 shows over a third (37%) of events involved some form of physical violence. Of the events that did involve physical violence, more than half (56%) resulted in a physical injury.

Table 5.16 Percentage of events that involved physical violence and physical injury

Type of event	Percentage of events (%)
Physical violence	37
With injury	*56*
Without injury	*44*
Non-violence	63

More than one offence type may occur within one event, or there may be multiple reasons for the event to come to the attention of the police. There were 12 variables in the dataset that recorded whether a particular offence or reason for reporting was present in each event. Multiple offence or event types could be recorded in one event. The presence of offence types and reporting reasons may be an underestimate if the factors were present but not recorded by the police. A verbal altercation was mentioned in the majority (80%) of events. The second most common factor to be mentioned was threats, in just under a quarter (23%) of events. Assault with injury was the third most mentioned, recorded in one in five (20%) events.

Table 5.17 Percentage of each offence type and/or reason for reporting across events

Type of offence/reason for report	Percentage of events (%)
Verbal altercation	80
Threats	23
Assault with injury	20
Assault without injury	17
Harassment	12
Breach	11
Criminal damage	9
Theft/unauthorised taking	7
Rape	1
Sexual assault/other offences	<1
Stalking	<1
Other	7

Crimed events

Crimed events were given a Home Office offence category, subclass and class, based on the 2020 notifiable offence list (Home Office, 2020a). Table 5.18 shows the most common type of offence category within crimed events was assault with injury, accounting for over a third (35%). The second most common category was assault without injury, accounting for over a quarter (28%), followed by harassment (11%).

Table 5.18 Percentage of crimed events in each Home Office offence category

Home Office offence category	Percentage of crimed events (%)
Assault with injury	35
Assault without injury	28
Harassment	11
Criminal damage to a dwelling	8
Burglary Residential	2
Malicious Communications	2
Other criminal damage	2
Public Fear Alarm or Distress	2
Threat/Possession with Intent to Commit Criminal Damage	2
Theft in Dwelling not auto machine	1
Threats to Kill	1
Assault with intent to cause serious harm	<1
Criminal damage to a building	<1
Criminal damage to a vehicle	<1
Other theft	<1
Racially Aggravated Assault without Injury	<1
Rape of a female aged 16 and over	<1
Reported incident of rape	<1
Theft from the person	<1
Theft/Unauthorised Taking	<1

Table 5.19 shows two-thirds (66%) of crimed events were classified as violence. Violence with injury was the most prevalent crime subclass (36%).

Table 5.19 Percentage of crimed events in each Home Office subclass

Home Office subclass	Percentage of crimed events (%)
Violence with injury	36
Violence without injury	30
Stalking/harassment	13
Criminal damage	13
Burglary residential	2
Other theft	2
Public order	2
Rape	1
Theft from the person	<1

Table 5.20 shows more than three quarters (78%) of crimed offences fell into the violence against the person offence class.

Table 5.20 Percentage of crimed events in each Home Office offence class

Home Office offence class	Percentage of crimed events (%)
Violence against the person	78
Arson and criminal damage	12
Theft	3
Burglary	2
Public order offences	2
Sexual offences	1
Miscellaneous crimes against society	1

Non-crimed events

Each non-crimed event was given a non-crimed event code. Table 5.21 shows more than half of non-crimed events were coded as a verbal altercation.

Table 5.21 Percentage of each event category in non-crimed events

Non-crimed event category	Percentage of non-crimed events (%)
Verbal altercation	54
Threats	13
Breach	9
Harassment	5
Assault without injury	4
Theft/unauthorised taking	2
Assault with injury	2
Rape	1
Criminal damage	<1
Sexual offences	0
Other	9

Circumstances

Frequency tables gave the prevalence of specific circumstances of events, relating to event location and the presence of children and witnesses. Table 5.22 shows the majority (83%) of events took place in the home address of the victim or perpetrator. The ‘other’ category included unlisted locations such as holiday resorts, and online locations such as social media platforms and text message.

Table 5.22 Percentage of events that took place in each location type

Location	Percentage of events (%)
Home address (of victim or perpetrator)	83
Outside/near home address	5
Other residential address (friend, relative, etc.)	4
Public place (nightclub, street, transport, etc.)	7
Other	2

Table 5.23 shows two-thirds (66%) of events were reported to the police by the victim. The second largest category was ‘other’ (19%). The ‘other’ category included reports from neighbours who overheard but did not witness the event, and reports from other agencies.

Table 5.23 Percentage of events reported by each informant type

Role of informant	Percentage of events (%)
Victim	66
Witness	11
Suspect	3
Both victim and suspect	2
Other	19

Data were missing for 1% of events, these cases were excluded

Children were recorded as present in just under a quarter (24%) of events. Any witness(es), including children, were recorded as present in 40% of events. Data were missing for 9% of events, these events were excluded from the count.

5.2.2. Are victims female and perpetrators male?

The analysis considered the prevalence, frequency and severity of DVA by and against females and males. The sex distribution of DVA is a core component of the ongoing debates within DVA theory, and the results of the following analyses are discussed in relation to these debates in the Discussion chapter.

5.2.2.1. Prevalence

Table 5.24 shows females accounted for just over half (53%) of victims in the dataset and less than a quarter (22%) of perpetrators.

Table 5.24 Percentage of female and male victims and perpetrators

	Females (%)	Males (%)	Total (%)
Percentage of victims	53	47	100 (n=68)
Percentage of perpetrators	22	78	100 (n=94)

A new variable was derived to denote the sex composition of each dyad. If the sex of the victim was female, and the sex of the perpetrator was male, the dyad sex composition was Female: Male, and so on. Table 5.25 shows over half of dyads (56%) involved a female victim and a male perpetrator.

Within Female:Male, 84% of perpetrators were a partner or ex-partner, 8% were the victim's brother, 3% were a parent, 3% were a son, no perpetrators were a grandparent, and the remaining 2% were classified as 'other'. Within Male:Female, 89% of perpetrators were a partner or ex-partner, 4% were a sister, 4% were a parent, no perpetrators were a daughter, no perpetrators were a grandparent and the remaining 4% were classified as ‘other’. Within Male:Male, 44% were a partner or ex-partner, 33% were brothers, 17% were a parent, 6% were a grandparent, no perpetrators were a son and no perpetrators were classified as ‘other’. Within Female:Female, 25% were a partner or ex-partner, 25% were a daughter, 25% were a sister, 25% were a parent, no perpetrators were a grandparent and no perpetrators were classified as ‘other’.

Table 5.25 Percentage of each dyad sex combination

Sex of dyad (Victim: Perpetrator)	Percentage of dyads (%)
Female: Male	56
Male: Female	24
Male: Male	16
Female: Female	4
Total	100 (n=110)

In some cases, the same two people accounted for two dyads in the dataset. In the dataset, there were 110 dyad ID numbers relating to 83 dyads due to oscillation between victim/perpetrator within the dyad where both persons were recorded as victim and as perpetrator during the series of events. Some cases of oscillation related to counter allegations. Counter allegations occur when the reported perpetrator alleges that the victim of the reported event also committed an offence against them (the perpetrator). To measure counter allegations in the dataset, they were recorded in a binary ‘Yes/No’ variable. The variable was recorded as ‘Yes’ when the police recorded in the free-text of an event that a counter allegation was made; when two cases (either two DA referrals and/or two crime reports) were recorded by the police for the same reported event with both parties[7] of the dyad recorded as a victim and perpetrator; and when both the victim and the perpetrator contacted police to report the same event. Where two events were recorded in the dataset, both were recorded as a counter allegation.

To investigate which dyad sex combinations had the highest proportion of counter allegations, a cross tabulation was produced of the counter allegation variable with the dyad sex variable. External cases (n=5) referred from other forces or organisations were excluded as any counter allegations may have been made to another force/organisation and therefore not counted in this dataset. Table

[7] Cases may involve more than one victim or perpetrator, the dyad is defined by the victim and suspect/offender stated in the DA referral.

5.26 shows the highest proportion of events (19%) that were recorded as counter allegations are in dyads with male victims and female perpetrators.

Table 5.26 Percentage of counter allegations by sex

Sex of dyad (Victim: Perpetrator)	**Counter allegation**			
	Yes (%)	**No (%)**	**Total (%)**	**n**
Female: Male	8	92	100	238
Male: Female	19	81	100	47
Male: Male	13	87	100	30
Female: Female	0	100	100	5
Total	10	90	100	320

5.2.2.2. Frequency

The frequency of DVA is here measured as the total number of DVA events suffered by victims, and committed by perpetrators. Table 5.27 gives the overall distribution of events per victim. Less than 10% of victims accounted for more than half (51%) of all recorded events.

Table 5.27 Distribution of events per victim

Number of incidents	Number of victims (% of victims)	Total number of incidents (% of incidents)
1	31 (46%)	31 (10%)
2	10 (15%)	20 (6%)
3	4 (6%)	12 (4%)
4	4 (6%)	16 (5%)
5	1 (1%)	5 (2%)
6	3 (4%)	18 (6%)
7	1 (1%)	7 (2%)
8	2 (3%)	16 (5%)
9	1 (1%)	9 (3%)
10	3 (4%)	30 (9%)
11	2 (3%)	22 (7%)
12	1 (1%)	12 (4%)
15	1 (1%)	15 (5%)
20	1 (1%)	20 (6%)
22	1 (1%)	22 (7%)
25	1 (1%)	25 (8%)
45	1 (1%)	45 (14%)
Total	**68 (100%)**	**325 (100%)**

Table 5.28 shows that as victims, females experienced more than three times as many events (247) of DVA than males (78). The average number of victimisations per female was more than three times (7) the average number of victimisations per male (2). As perpetrators, males accounted for more than five times (273) the number of events than females (52). The average number of events per male perpetrator was twice (4) the average number of events per female perpetrator.

Table 5.28 Average number of events for victims and perpetrators, by sex

	Females	Males
Victims		
Minimum	1	1
Mean	7	2
Median	3	1
Maximum	45	15
Total	**247**	**78**
Perpetrators		
Minimum	1	1
Mean	2	4
Median	1	2
Maximum	11	18
Total	**52**	**273**

5.2.2.3. Severity

Five measures of severity were examined: crimed and non-crimed, violence (with and without injury) and non-violence, and three offence severity scales: seriousness scores (Francis et al, 2005), Cambridge Crime Harm Index (CHI) (Sherman et al, 2016), and Costs of Crime Harm Index (Heeks et al, 2018). A description of each severity measure is given in the Methods chapter. For the first two measures, the percentage of crimed and violent incidents that were against/by females and males is given. For the severity scales, the average and maximum severity scores of events against and by females and males are compared.

Crime and non-crime

Table 5.29 shows that around half (51%) of events reported to the police were crimed for both female and male victims, and around half were crimed by female (50%) and male (51%) perpetrators.

Table 5.29 Percentage of events that were crimed, by sex

	Females (%)	Males (%)
Victims		
Crimed	51	51
Non-crimed	49	49
Perpetrators		
Crimed	50	51
Non-crimed	50	49

Violence and non-violence

Violence was measured using a three-level variable (non-violence, violence without injury, violence with injury). Table 5.30 shows that 17% of events against female victims were recorded as violence that resulted in physical injury, compared to 31% of events against males. 25% of events perpetrated by females were recorded as violence that resulted in physical injury, compared to 20% of events perpetrated by males. Though a higher proportion of events against male victims were recorded as violence with injury, most violence in the dataset was perpetrated by males against female victims, as female victims experienced and male victims perpetrated the majority of events in the data.

Table 5.30 Percentage of events that were recorded as violence, by sex

	Females (%)	Males (%)
Victims		
Violence with injury	17	31
Violence without injury	16	18
Non-violence	66	51
Perpetrators		
Violence with injury	25	20
Violence without injury	14	17
Non-violence	62	63

Severity scales

The average severity of events against and by females and males using the seriousness scores (Francis et al, 2005) are presented in Table 5.31. The measures of central tendency gave different results. For victims, the mean event severity was slightly higher for females (2.7) than for males (2.6), though the median event severity for females (3.0) was lower than the median for males (4.0). Females suffered the most severe event(s), with a maximum severity score of 8.0, compared to 6.0 for males. The highest score in the scale is 8.0 and was given for rape. A score of 6.0 may relate to robbery, burglary, or other sexual offences (see Methodology for scores). For perpetrators, the mean event severity score was slightly lower for females (2.5) than for males (2.7), though the median event severity score was equal (3.0). Males perpetrated the most severe event(s), with a maximum severity score of 8.0 compared to 6.0 for females.

Table 5.31 Average severity of events using Francis et al (2005) seriousness scores, by sex

	Females	Males
Victims		
Minimum	0	0
Mean	2.7	2.6
Median	3.0	4.0
Maximum	8.0	6.0
Perpetrators		
Minimum	0	0
Mean	2.5	2.7
Median	3.0	3.0
Maximum	6.0	8.0

The average severity scores using the CHI (Sherman et al, 2016) are presented in Table 5.32. For victims, the mean severity of events suffered by females (62.2) was higher than the mean for males (59.3), the median was the same (1.0). The most severe events were suffered by females, with a maximum severity score of 1825.0, compared to 1460.0 for males. The score of 1825.0 was the highest in the scale, given for rape. A score of 1460.0 was given to some subtypes of violence with injury, including actual bodily harm. For perpetrators, the average severity of events perpetrated by females (86.9) was higher than for males (56.7). Males perpetrated the most severe events, with a maximum severity score of 1825.0, compared to 1460.0 for females.

Table 5.32 Average severity of events using the Cambridge Crime Harm Index, by sex

	Females	Males
Victims		
Minimum	0	0
Mean	62.2	59.3
Median	1.0	1.0
Maximum	1825.0	1460.0
Perpetrators		
Minimum	0	0
Mean	86.9	56.7
Median	1.0	1.0
Maximum	1460.0	1825.0

The average severity scores using the Costs of Crime Harm Index (Heeks et al, 2018) are presented in Table 5.33. For victims, the mean event severity score was lower for females (5.9) than for males (6.7), though the median severity scores were equal (6.8). Females suffered the most severe events, with a maximum event severity score of 45.0, compared to 16.1 for males. The score of 45.0 was the highest in the scale, given for rape. A score of 16.1 was given for violence with injury. For perpetrators, the mean event severity score was slightly higher for males (6.1) than for females (6.0). The median event severity for male perpetrators is higher (6.8) than the median for females (4.2). Males perpetrate the most severe events, with a maximum severity score of 45.0, compared to 16.1 for females.

Table 5.33 Average severity of events using the Costs of Crime Harm Index, by sex

	Females	Males
Victims		
Minimum	0	0
Mean	5.9	6.7
Median	6.8	6.8
Maximum	45.0	16.1
Perpetrators		
Minimum	0	0
Mean	6.0	6.1
Median	4.2	6.8
Maximum	16.1	45.0

5.2.2.4. Summary

Females accounted for just over half (53%) of victims, yet experienced the majority (76%) of all DVA events. Males accounted for more than three quarters (78%) of perpetrators and the majority (84%) of events. DVA repetition was predominantly against females and by males. Regarding severity, a higher percentage of events against male victims were recorded as physical violence with injury, than of events against female victims, though female victims experienced the majority of both violent and non-violent events. The average severity of events experienced and perpetrated by females and males varied by the severity scale and measure of central tendency, though across all scales, females experienced and males perpetrated the most severe forms of DVA. This is due to the inclusion of the sexual offence of rape, which across all severity scales was the highest scoring offence type present in the data, and was only perpetrated by males and against female victims in this dataset.

5.2.3. Does DVA escalate?

As discussed in the Literature Review, there are competing debates on whether DVA escalates in frequency and/or severity, and whether escalation is a characteristic of different forms of DVA. Three hypotheses of DVA escalation trajectories were derived from the literature, presented in the following subsection. To address the question and test the hypotheses, escalation was measured through descriptive and statistical analyses. Descriptive analyses first examined the prevalence of escalation variables in the dataset to identify any evidence of change in frequency and severity for repeat DVA. Trajectories of escalation were then manually plotted and categorised for repeat dyads to descriptively consider the hypotheses. Escalation trajectories were then statistically modelled to test the three hypotheses. The escalation of DVA is a core component of ongoing debates in DVA theory, thus the results of the subsequent analyses are considered in relation to existing literature in the Discussion chapter.

5.2.3.1. Hypotheses of escalation trajectories

Key theories in the literature were simplified into hypotheses that state DVA follows one trajectory of escalation (Walby and Towers); there are two DVA trajectories, one that escalates and one that remains stable (Johnson); there are three DVA trajectories with a low-frequency/severity stable trajectory, a high-frequency/severity trajectory, and a time-limited trajectory that escalates and then de-escalates in frequency and/or severity (Nagin and Land). The DVA literature has focused on the trajectories of victimisation (Walby and Towers, Johnson), and the criminal careers approach (Nagin and Land) has focused on offenders. The three hypothesised trajectories in Table 5.34 were tested for *dyad* trajectories, accounting for both offenders and victims.

Table 5.34 Three hypotheses for escalation trajectories

Three hypotheses for escalation trajectories in the DVA dataset
1. DVA has one trajectory that escalates in frequency and/or severity over time
2. There are two DVA trajectories: one that escalates in frequency and/or severity over time, and one that does not escalate and remains stable in frequency and/or severity
3. There are three DVA trajectories: one that escalates over time, one that remains stable over time, and one that desists or de-escalates in frequency and/or severity over time

5.2.3.2. Escalation between the first and last recorded event

The first measure of escalation compared the prevalence of variables of escalation in the first and last recorded DVA event for repeat dyads. There were five binary variables of escalation derived in the dataset shown in Table 5.35. Each was a binary ‘Yes/No’ variable. If a variable was recorded as ‘Yes’ in an event for a dyad, the variable was recorded as present for all subsequent events relating to that dyad. A risk classification variable coded the risk classification allocated to each event by the police (standard, medium, high).

Table 5.35 shows that in the first recorded event, more than one in ten (16%/12%) victims stated that the abuse was happening more often and/or was getting worse. This increased to more than a quarter (29%/28%) of victims in the last event. In the first recorded event, 6% of perpetrators in repeat dyads had used weapons against the victim in the current or in a previous event. By the last recorded event, an additional 20% of perpetrators had used weapons against the victim. In the first recorded event, 8% of perpetrators had made threats to kill the victim or someone else, this increased to more than 20% of perpetrators by the last recorded event. In the first event, 12% of perpetrators had attempted to strangle/choke/suffocate/drown the victim in a past event. By the last event, this increased to over a quarter (29%). In the first event for repeat dyads, the police classified almost three quarters of events (73%) as standard-risk, and only 6% as high-risk. By the last event, the percentage recorded as medium-risk increased from 22% to 26% and the percentage recorded as high-risk from 6% to 31%.

Table 5.35 Derived measures of escalation in the first and last event

Measure of severity	First event (Yes) (%)	Last event (Yes) (%)
Is the abuse happening more often?	16	29
Is the abuse getting worse?	12	28
Has the perpetrator ever used weapons or objects to hurt the victim?	6	26
Has the perpetrator ever threatened to kill the victim or someone else?	8	22
Has the perpetrator ever attempted to strangle/choke/suffocate/drown the victim?	12	29
Standard-risk	73	43
Medium-risk	22	26
High-risk	6	31

Across all derived measures of severity, the percentage of dyads with the measure recorded was higher in the most recent recorded event than in the first recorded event. Therefore, for at least some dyads, the frequency and/or severity of DVA increased between the first and the last recorded event. The increase in the percentage of events classified as medium or high-risk in the most recent event shows that the police perception of risk increased between the first and last recorded event for at least some dyads. The analysis did not account for fluctuations in frequency or severity between the first and last event.

5.2.3.3. Descriptive escalation trajectories

The first phase of trajectory modelling was descriptive. All dyads with two or more events were included (n=51). Some victims appear in more than one dyad due to victimisation from multiple perpetrators. For each dyad, each recorded DVA event was plotted by date and level of severity to produce a trajectory of frequency and severity over time. The trajectory shows the rate of change in severity based on the three-level severity classification of each event, and a rate of change in frequency based on the proximity of events by date. The three-level measure is shown in Table 5.36.

Table 5.36 Three-level measure of DVA event severity

Severity value	Event type
1	No physical violence
2	Physical violence, no injury to victim
3	Physical violence, injury to victim

The plotted trajectories were manually grouped based on similar visual patterns of frequency and/or severity. From the manual grouping, four trajectories of escalation were derived.

Four trajectory classifications

1. Escalation in frequency and/or severity
2. De-escalation in frequency and/or severity
3. Stability in frequency and/or severity
4. Fluctuation in frequency and/or severity

Each dyad trajectory is presented here.

5.2.3.3.1. Escalation trajectories

Each escalation shows an increase in the severity and/or frequency of events over time. An increase in severity was determined when the severity of the most recent events appeared to be higher than the severity of the earliest events in the trajectory. An increase in frequency was determined when there was a higher rate of occurrence in the most recent events than the earliest events, based on the proximity of event dates.

Figure 5.2 Dyad 1a escalation

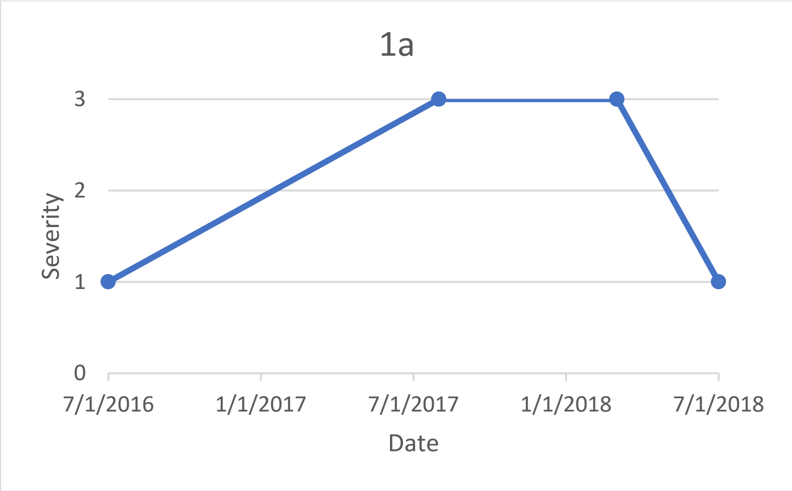


Figure 5.1 Dyad 16a escalation

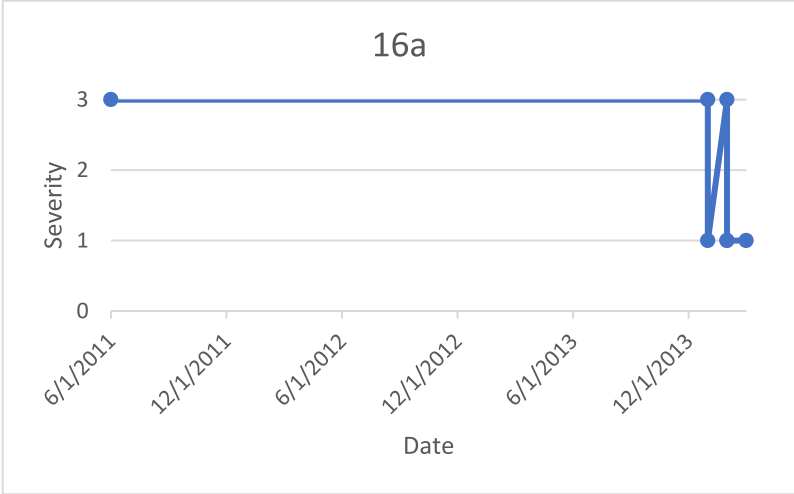


Figure 5.4 Dyad 19a escalation

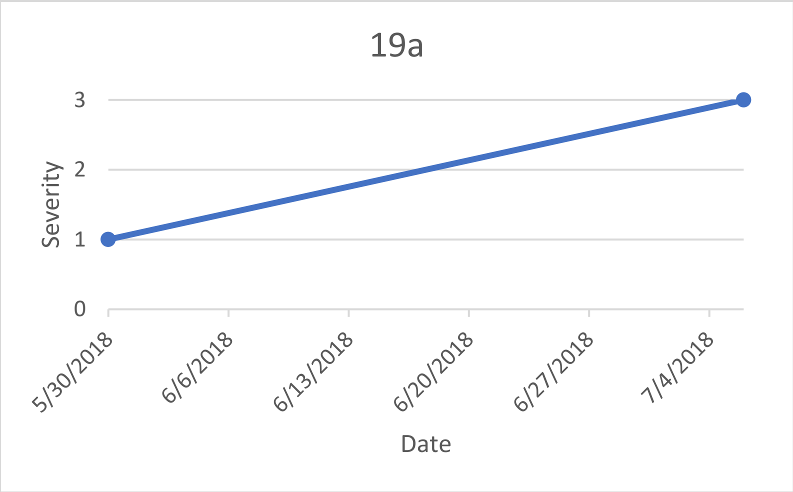


Figure 5.3 Dyad 20a escalation

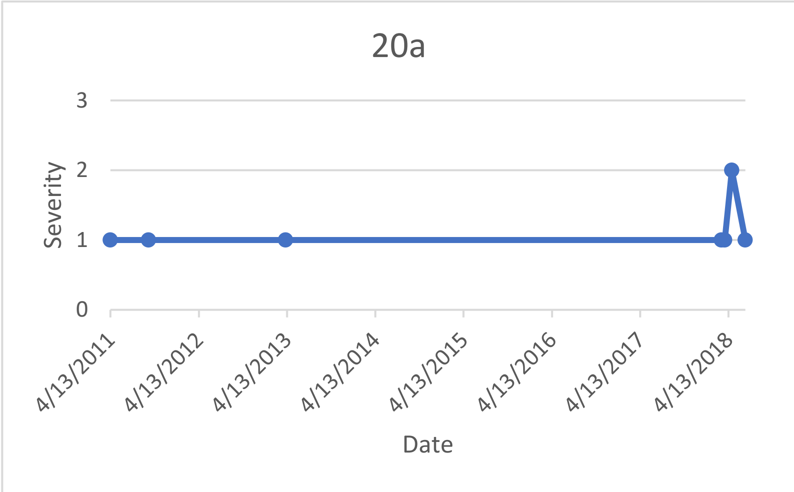


Figure 5.6 Dyad 26a escalation

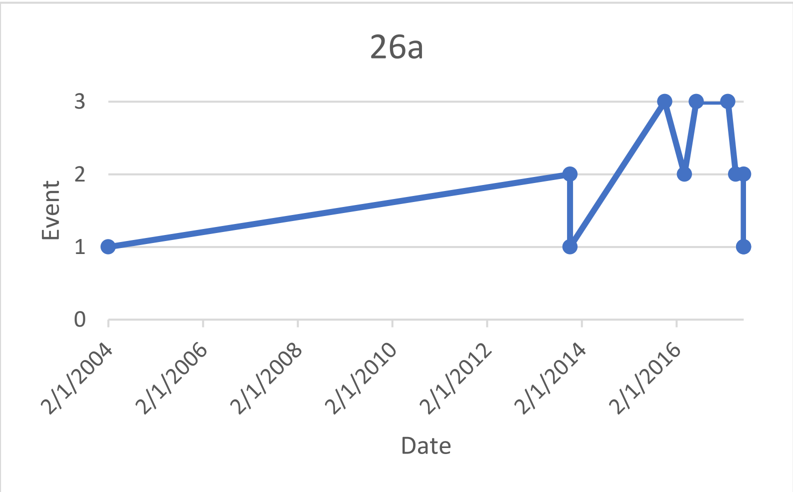


Figure 5.5 Dyad 27a escalation

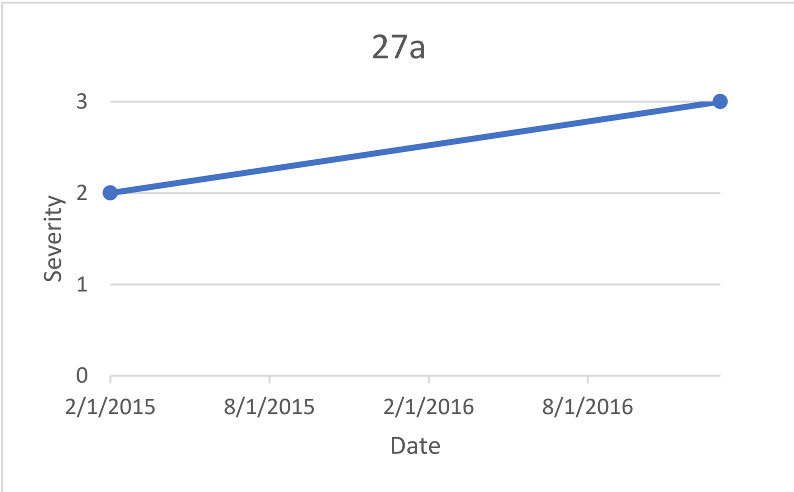


Figure 5.8 Dyad 43a escalation

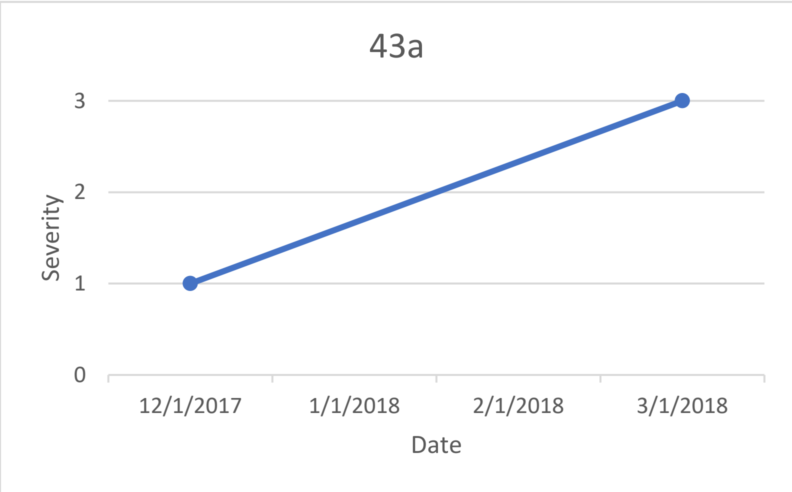


Figure 5.7 Dyad 51a escalation

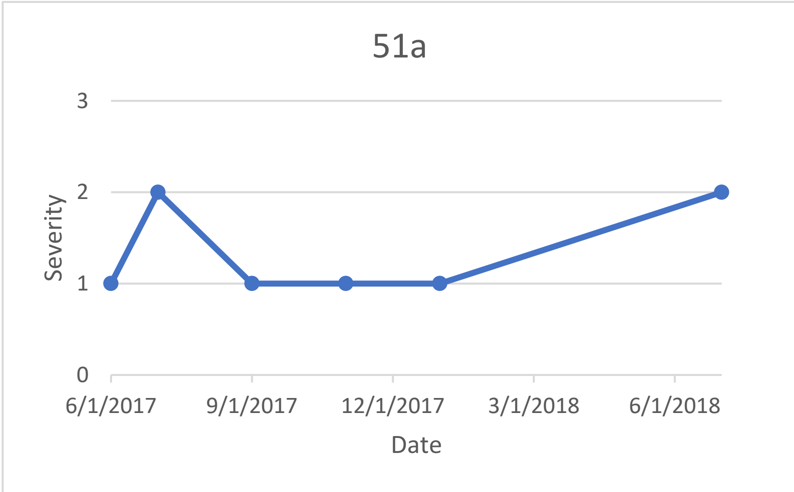


Figure 5.10 Dyad 54a escalation

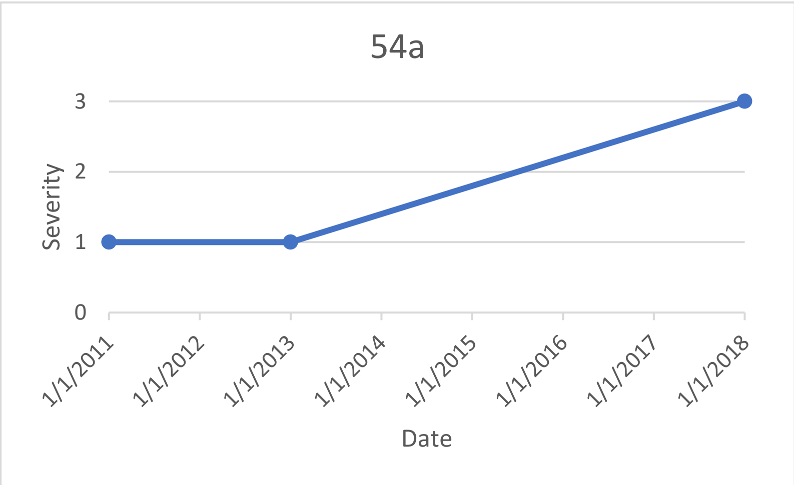


Figure 5.9 Dyad 56a escalation

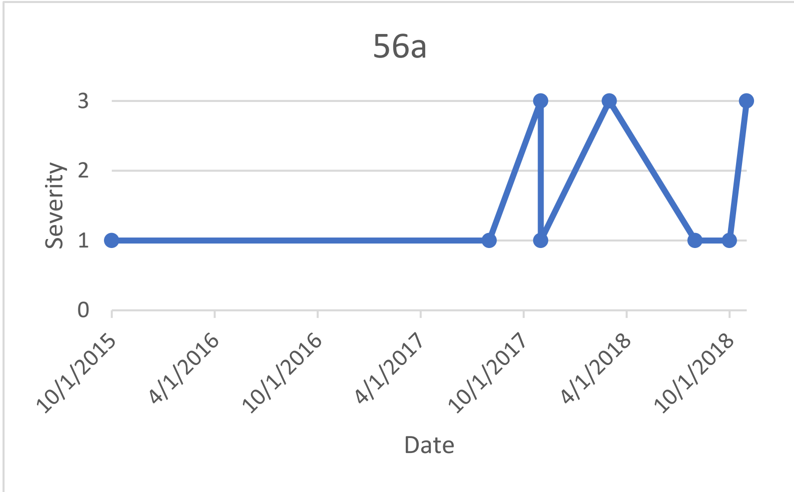


Figure 5.12 Dyad 56b escalation

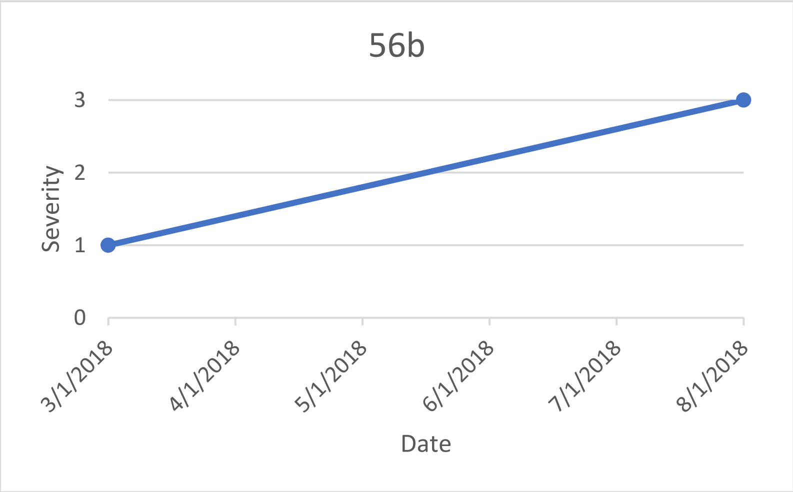


Figure 5.11 Dyad 59b escalation

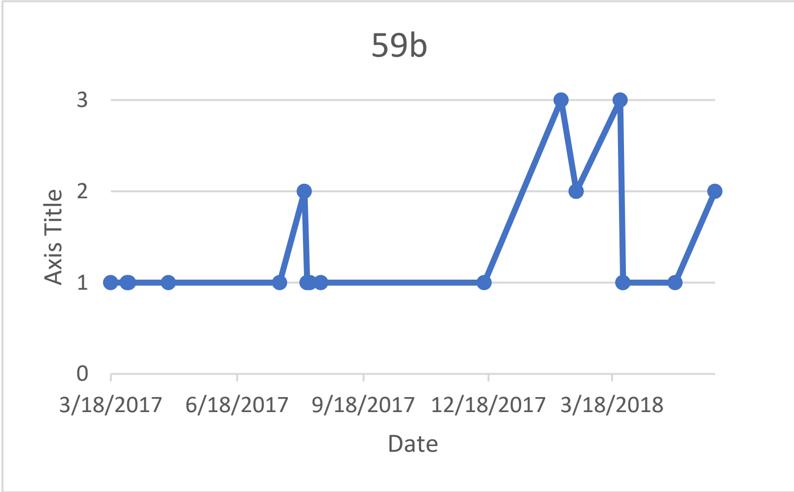


Figure 5.14 Dyad 68b escalation

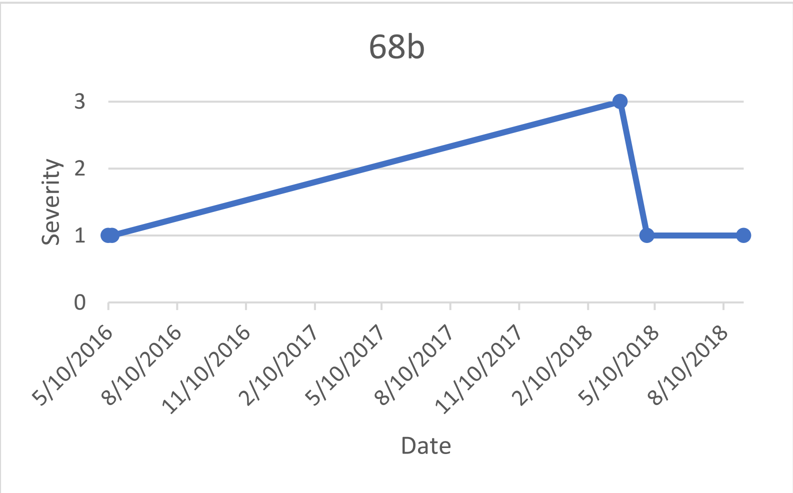


Figure 5.13 Dyad 69b escalation

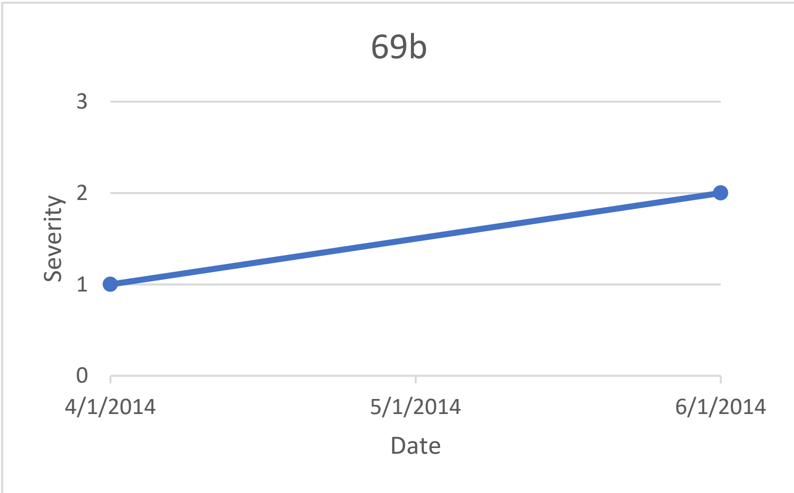


Figure 5.16 Dyad 81b escalation

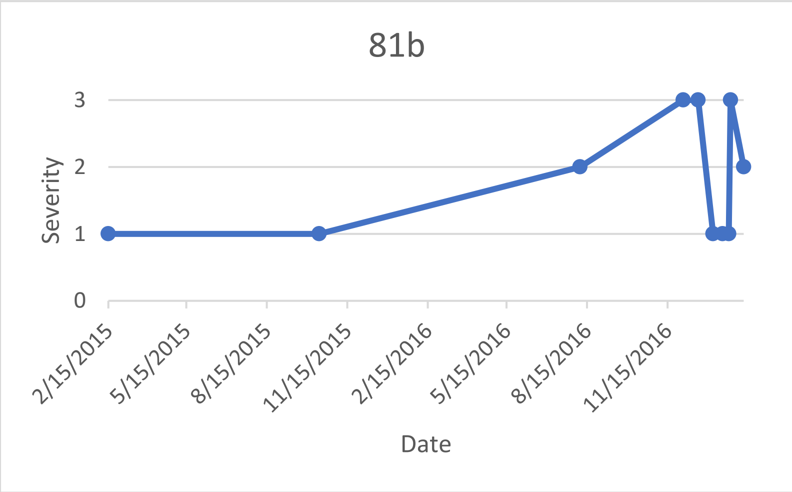
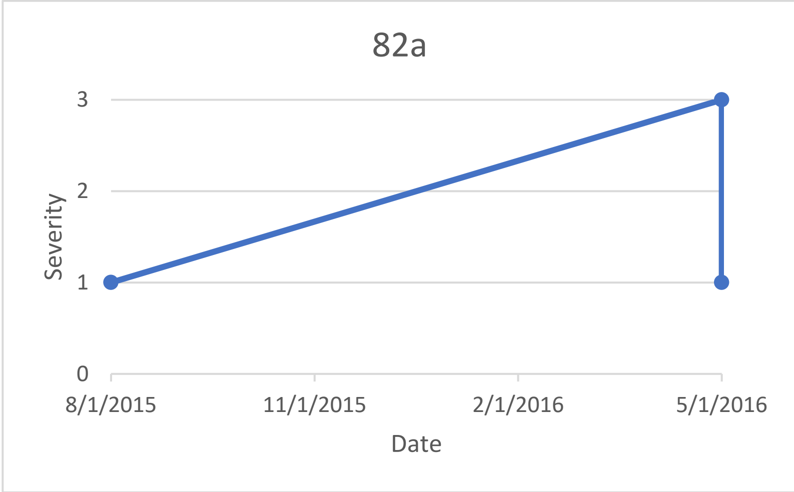


Figure 5.15 Dyad 82a escalation



5.2.3.3.2. De-escalation trajectories

Each de-escalation shows a decrease in the severity and/or frequency of events over time. A decrease in severity was determined when the severity of the most recent events appears to be lower than the severity of the earliest events in the trajectory. A decrease in frequency was determined when there was a lower rate of occurrence in the most recent events than the earliest events, based on the proximity of event dates.

Figure 5.18 Dyad 2a de-escalation

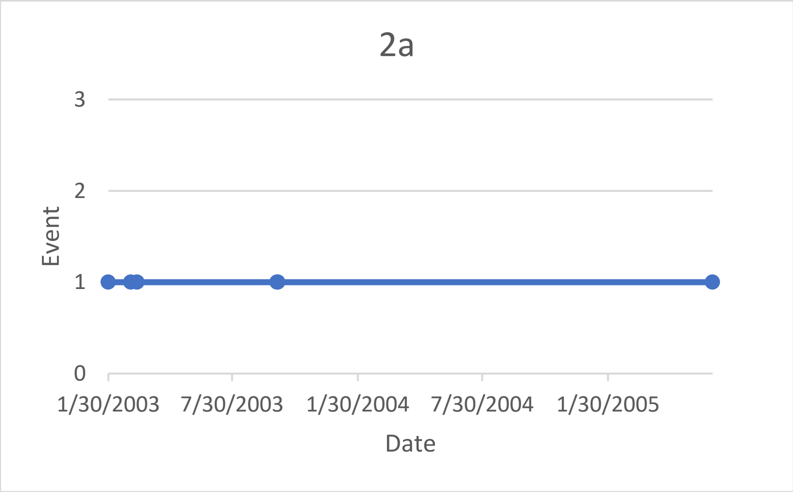


Figure 5.17 Dyad 31a de-escalation

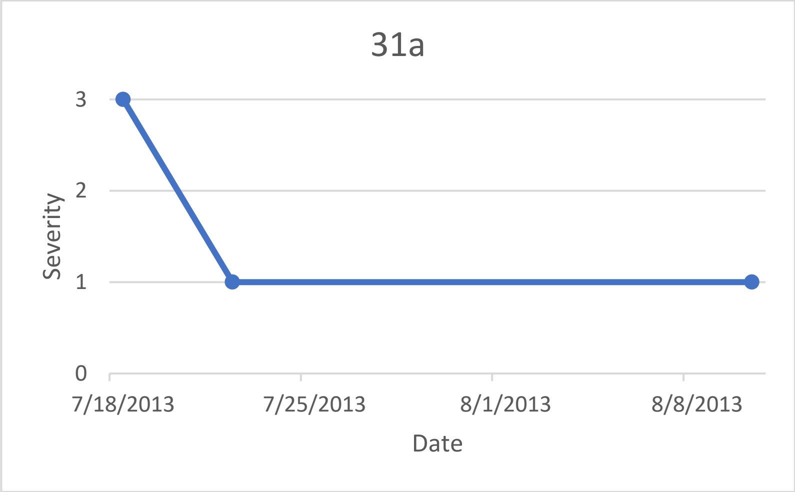


Figure 5.20 Dyad 33a de-escalation

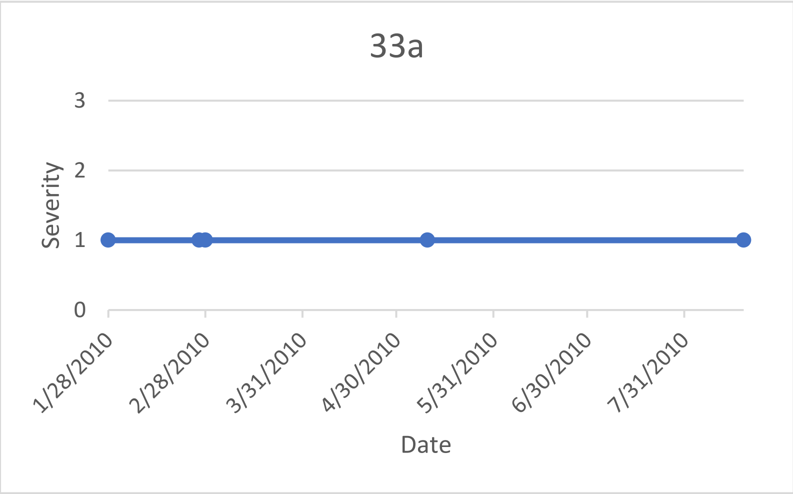


Figure 5.19 Dyad 38a de-escalation

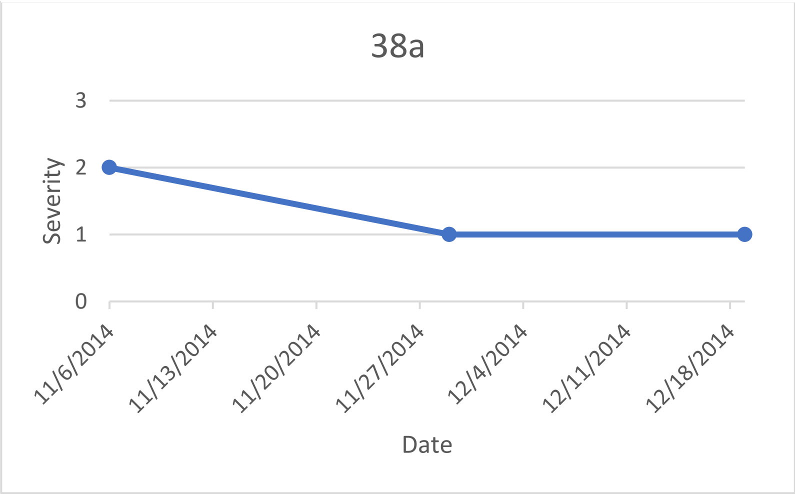


Figure 5.22 Dyad 50a de-escalation

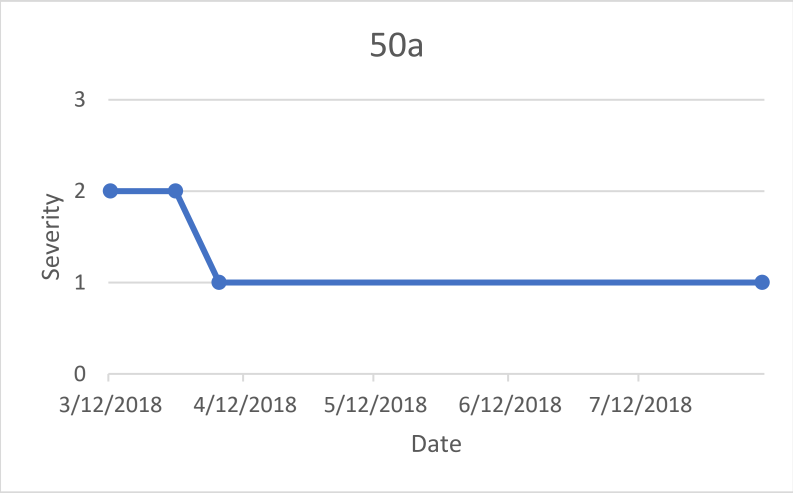


Figure 5.21 Dyad 52a de-escalation

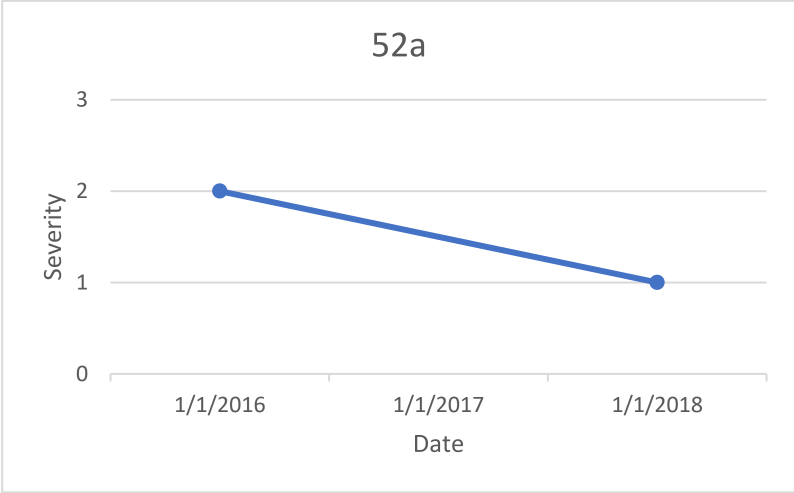


Figure 5.24 Dyad 59a de-escalation

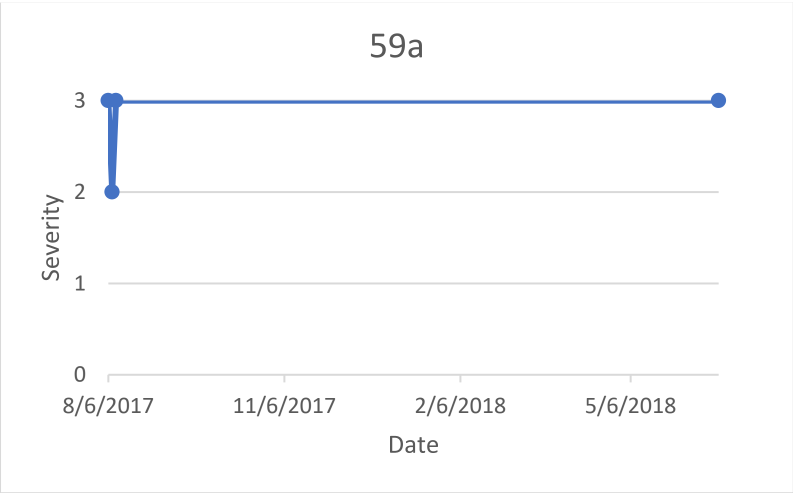


Figure 5.23 Dyad 61a de-escalation

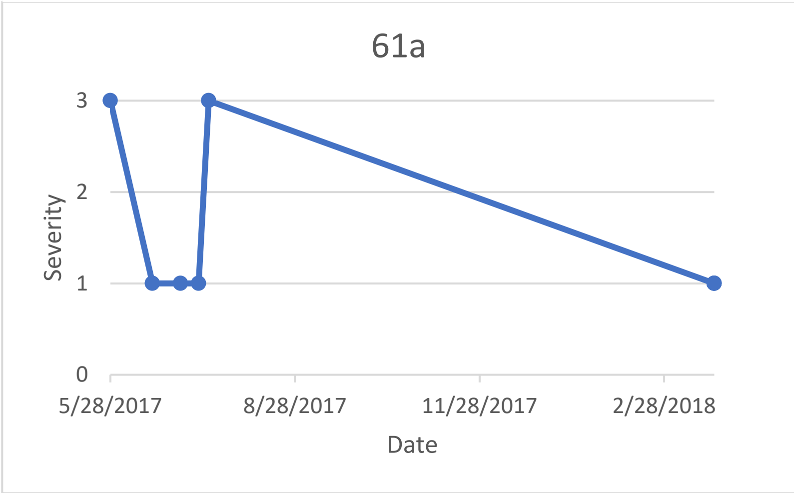
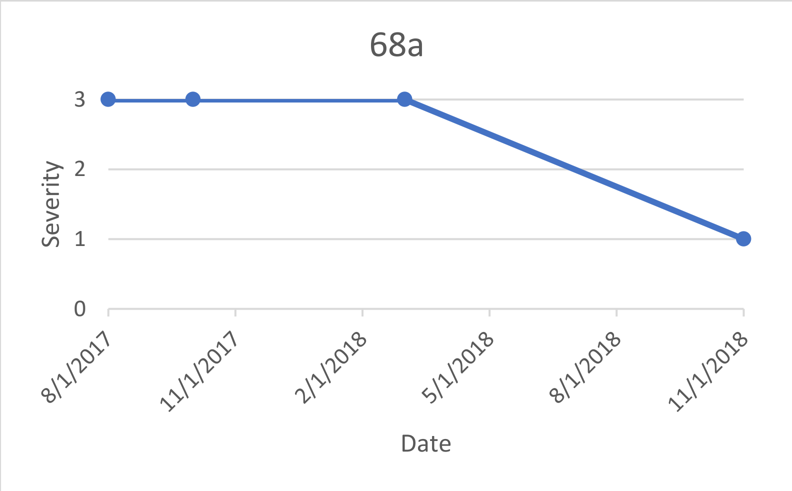


Figure 5.25 Dyad 68a de-escalation



5.2.3.3.3. Stable trajectories

Each stable trajectory shows a lack of change in the severity and/or frequency of events over time. For each stable trajectory, all recorded events were non-violent. The number of events in stable trajectories tended to be lower than the number of events in other trajectory classifications, and there was little to no change in the rate of occurrence over time. Stability was determined by the lack of change in the rate of occurrence from the earliest events to the most recent events in the trajectory.

Figure 5.27 Dyad 4a stable

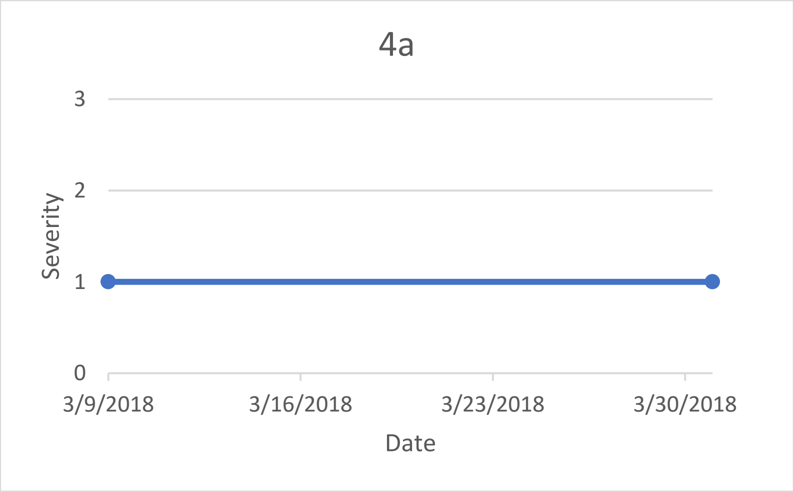


Figure 5.26 Dyad 7a stable

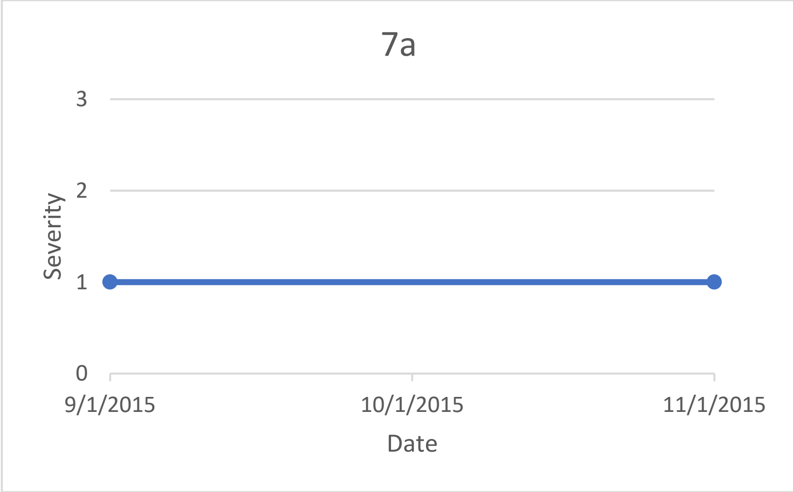


Figure 5.29 Dyad 9a stable

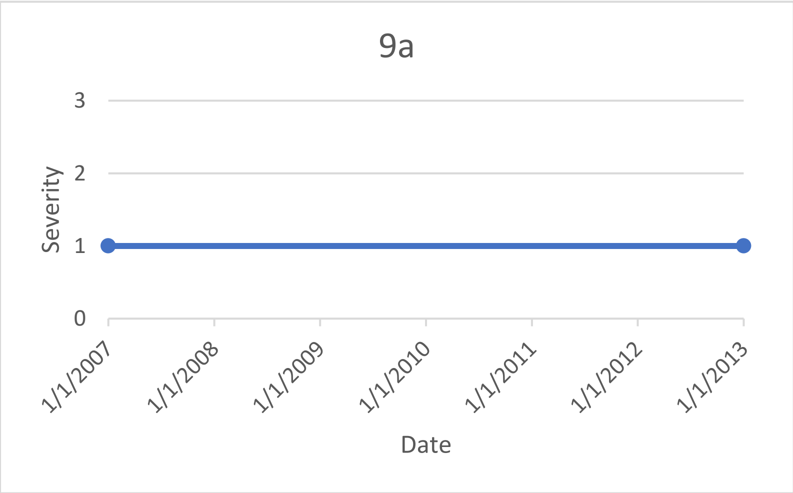


Figure 5.28 Dyad 10b stable

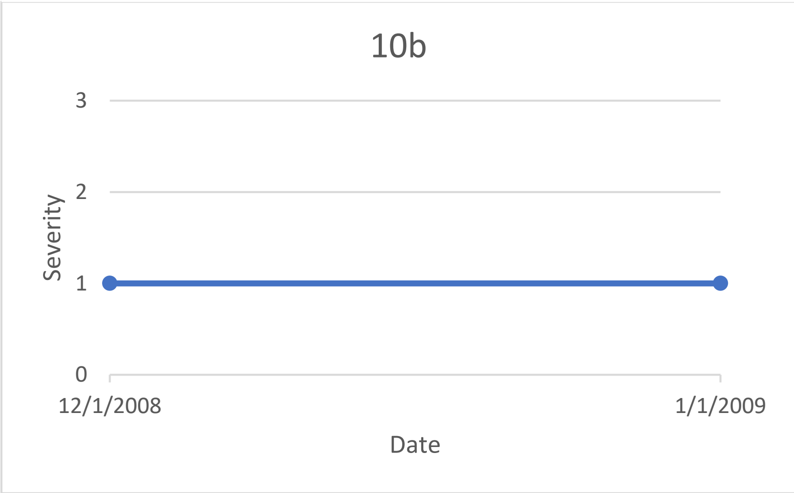


Figure 5.33 Dyad 13a stable

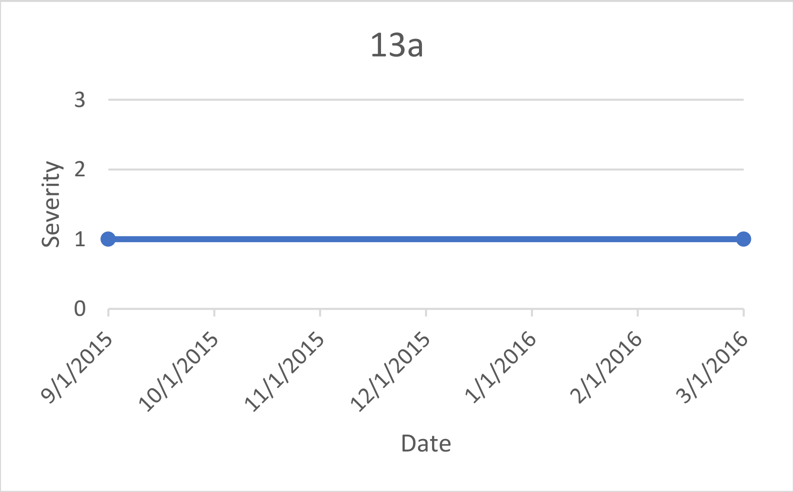


Figure 5.32 Dyad 26b stable

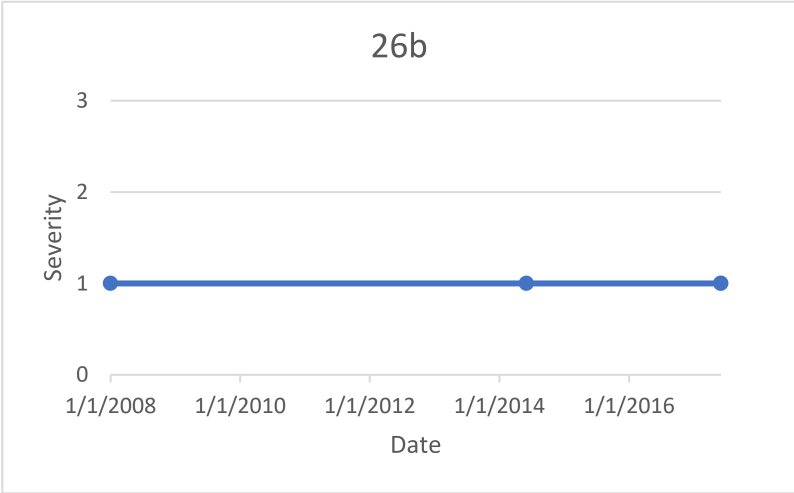


Figure 5.31 Dyad 29a stable

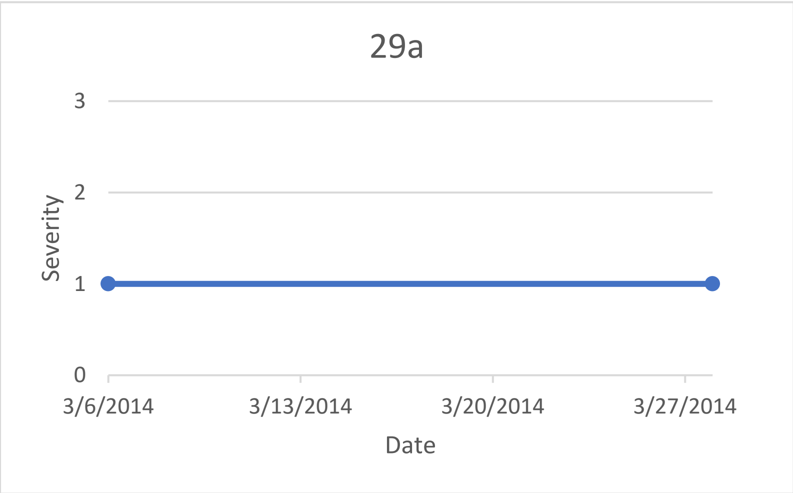


Figure 5.30 Dyad 32a stable

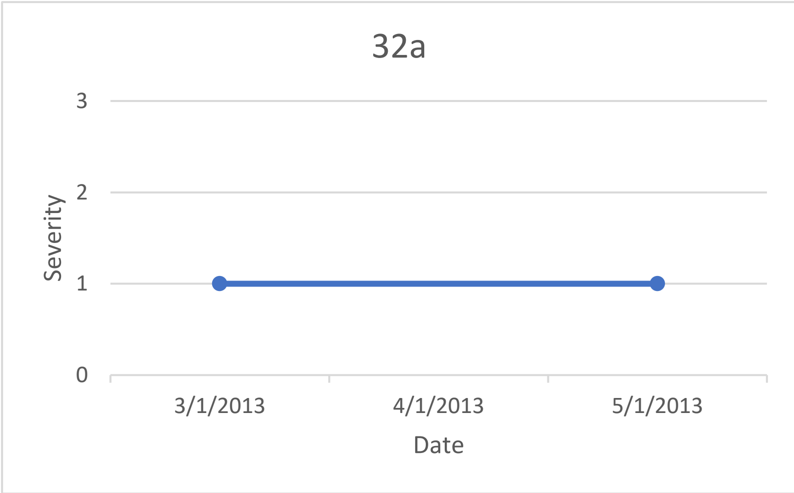


Figure 5.35 Dyad 35a stable

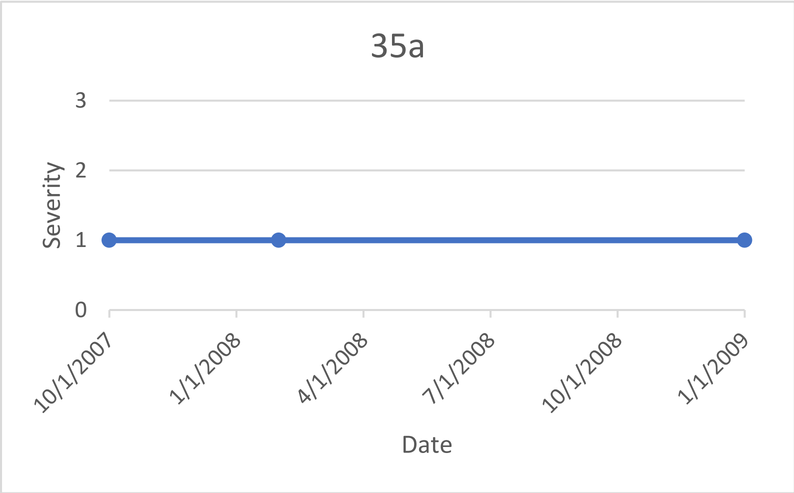


Figure 5.34 Dyad 37a stable

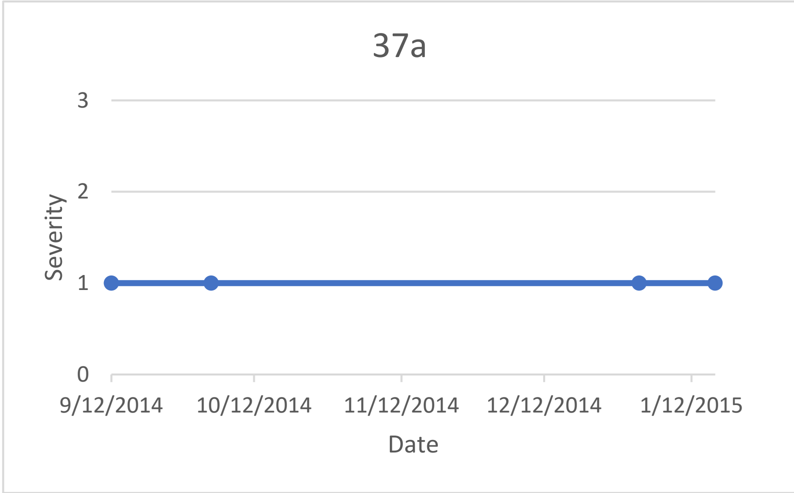


Figure 5.37 Dyad 48a stable

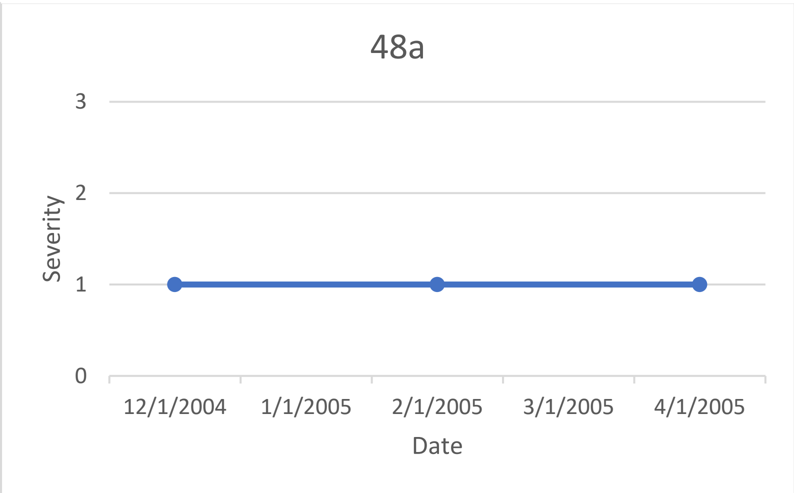


Figure 5.36 Dyad 49a stable

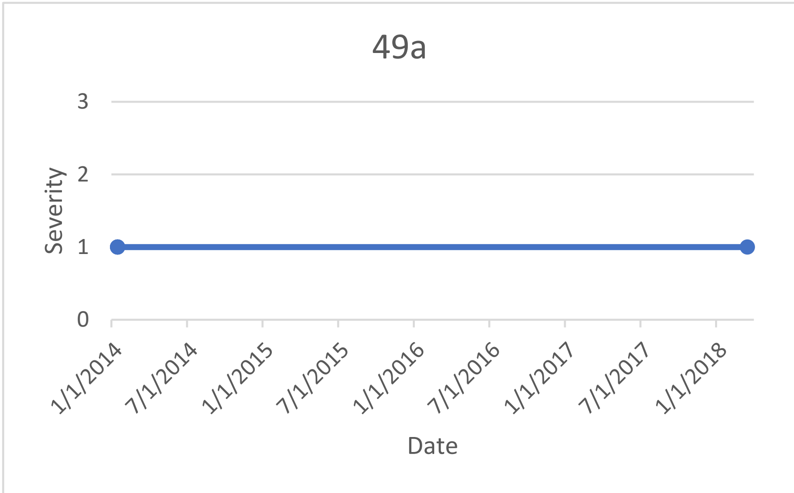


Figure 5.40 Dyad 57a stable

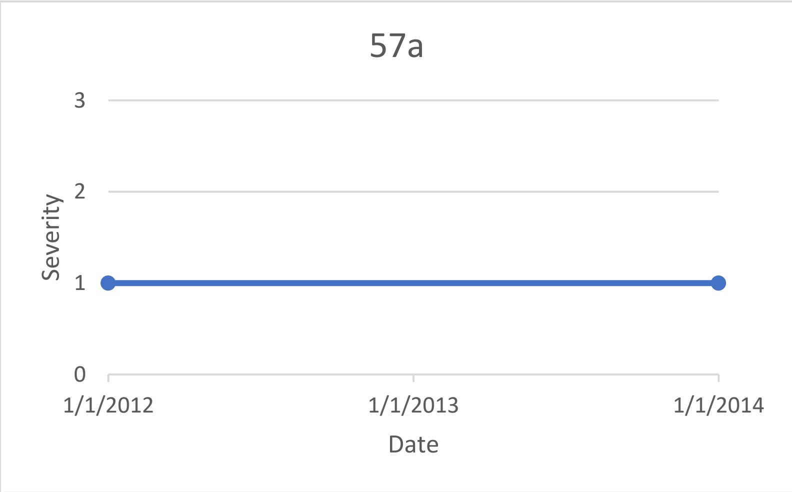


Figure 5.39 Dyad 60b stable

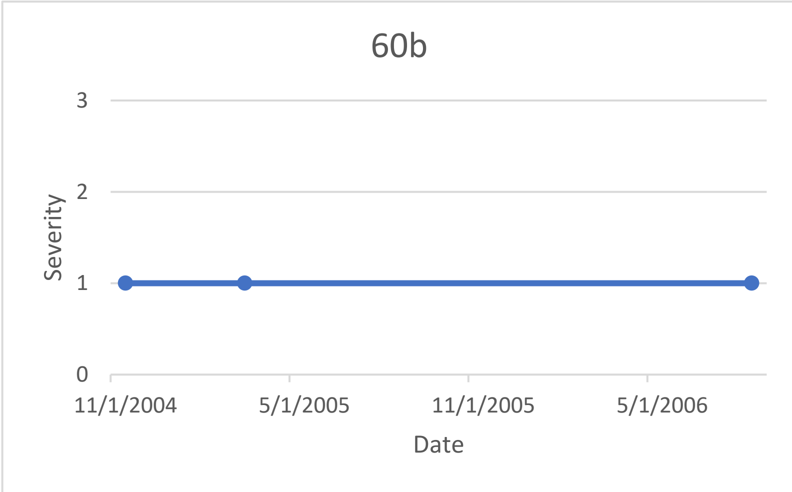
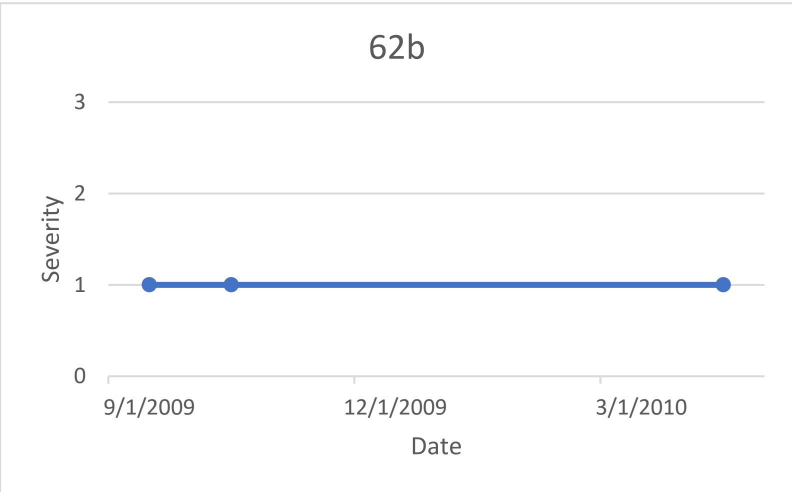


Figure 5.38 Dyad 62b stable



5.2.3.3.4. Fluctuating trajectories

Each fluctuating trajectory shows a changing rate of severity and/or frequency at different points within the trajectory, with periods of both escalation and de-escalation.

Figure 5.42 Dyad 8a fluctuating

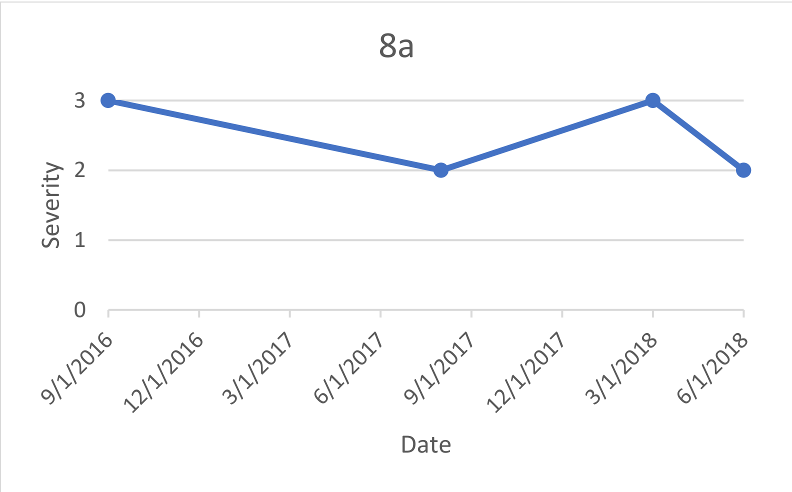


Figure 5.41 Dyad 15a fluctuating

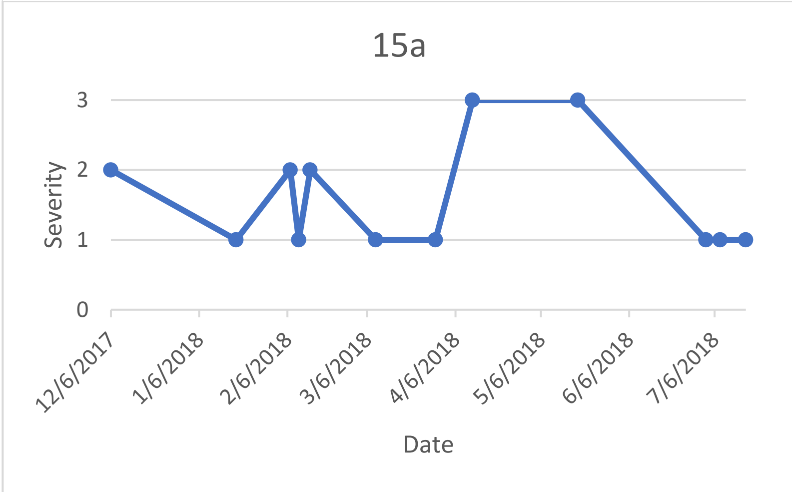


Figure 5.44 Dyad 30a fluctuating

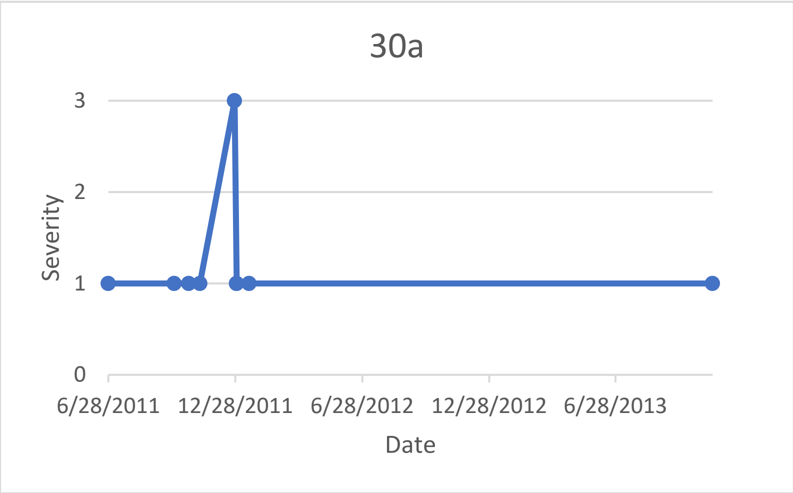


Figure 5.43 Dyad 35b fluctuating

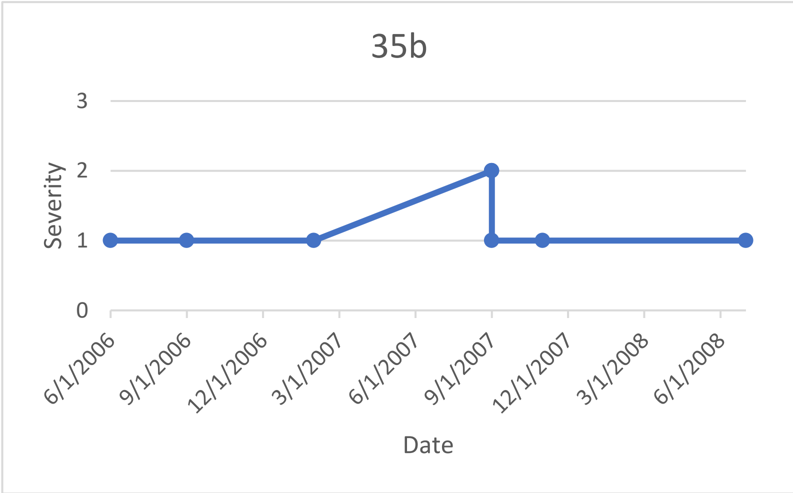


Figure 5.46 Dyad 36a fluctuating

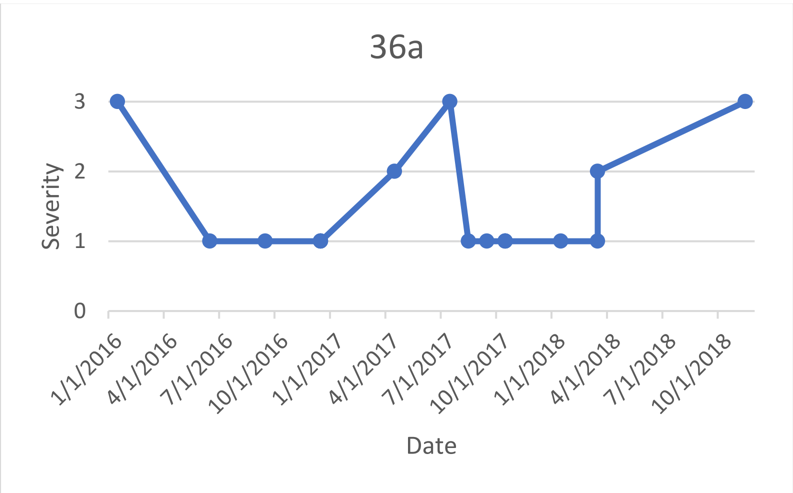


Figure 5.45 Dyad 55a fluctuating

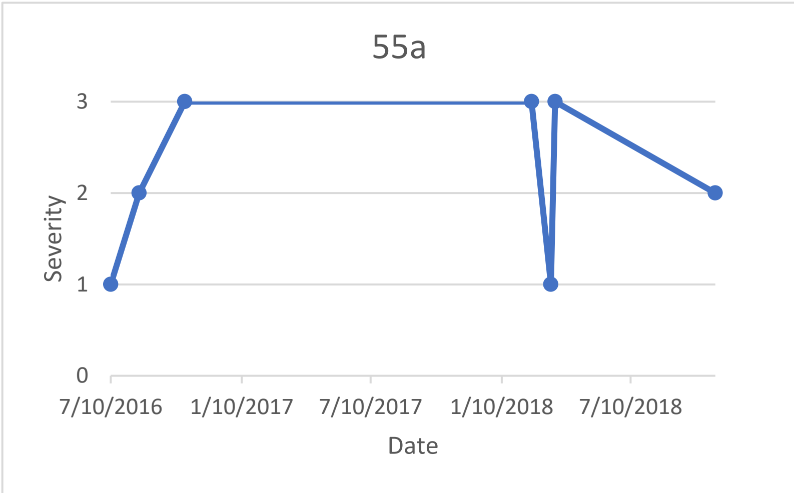


Figure 5.48 Dyad 58a fluctuating

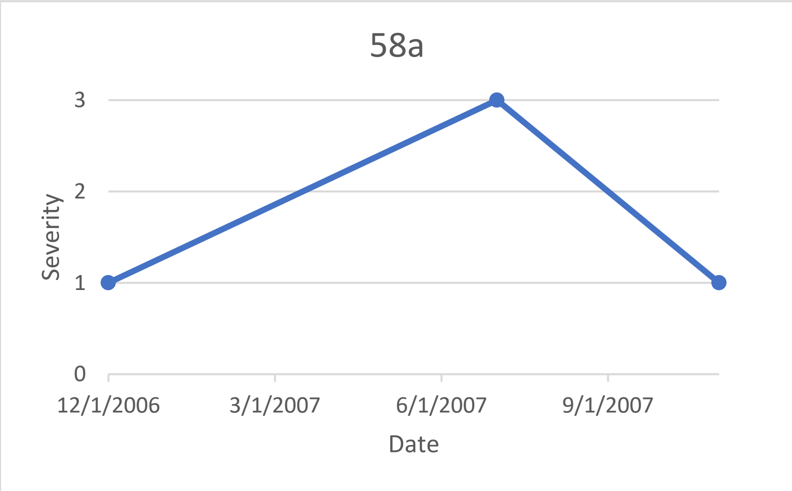


Figure 5.47 Dyad 64b fluctuating

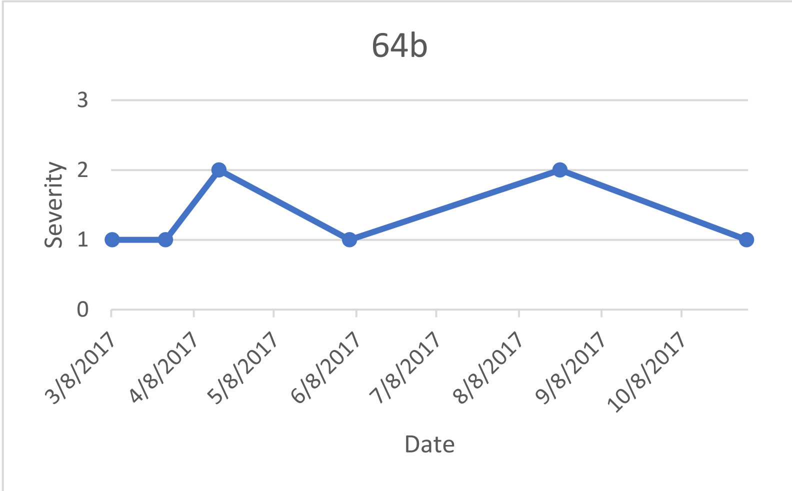


Figure 5.50 Dyad 71a fluctuating

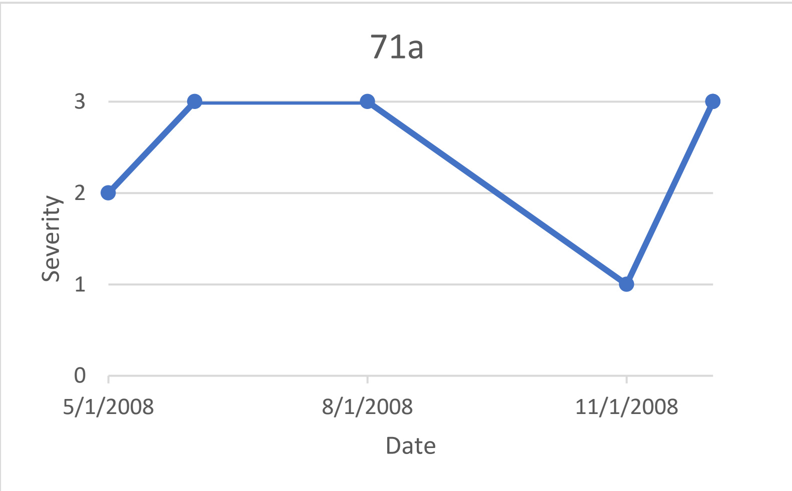


Figure 5.49 Dyad 79a fluctuating

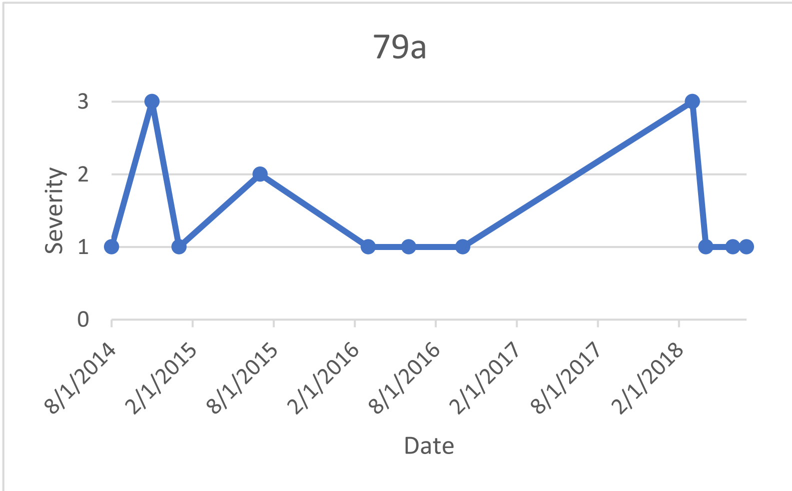
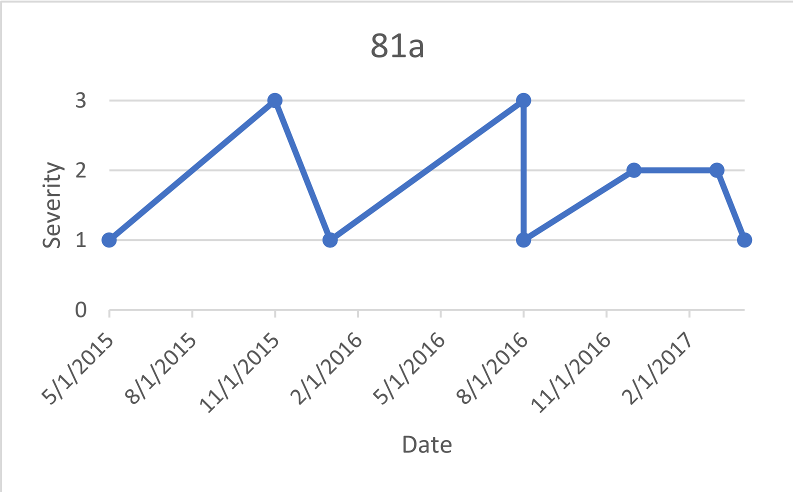


Figure 5.51 Dyad 81a fluctuating



5.2.3.3.5. Summary of descriptive trajectories

The four trajectory patterns do not support the hypotheses that there are between one and three DVA trajectories. There was evidence of escalating, de-escalating and stable trajectories, but the fluctuating trajectories were not accounted for by the hypotheses. The descriptive analysis differs to previous analyses of offending or victimisation trajectories (e.g. Nagin and Land) as this analysis focused on individual DVA series per dyad with differing numbers of events covering varying lengths of time, rather than modelling trajectories using data from multiple dyads, victims or perpetrators. The method of analysis may contribute to the presence of a fluctuating trajectory category. Furthermore, the analysis may be affected by the inclusion of multiple dyads that are not independent of one another e.g. victims appearing in multiple dyads, oscillation between dyads. In the second stage of trajectory analyses, a subset of repeat victims was taken to mitigate for any possible effects caused by overlapping dyads.

5.2.3.4. Latent trajectories of frequency

Trajectories of escalation were statistically modelled using latent trajectory analysis. Frequency and severity were modelled separately. The data were firstly filtered to only include dyads with two or more events (n=51). For victims with multiple dyads, the most recent repeat dyad was taken and previous dyads are omitted from the data (n=20). A follow-up period of three-years was selected from the point of the first recorded event for each dyad. If there was more than three years between the first and second recorded event, the dyad was omitted (n=1). There were 30 dyads that met the inclusion criteria for the analysis.

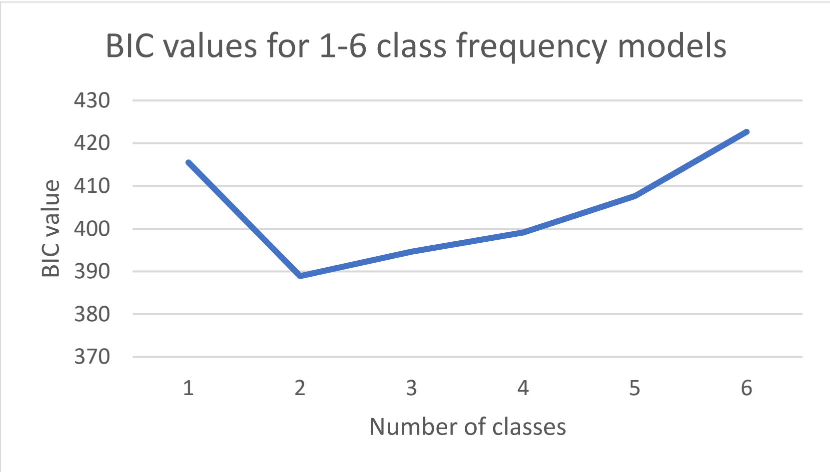
Frequency was measured as the number of events recorded within each six-month time-point over three years. Six regression models with between 1 – 6 trajectory groups were estimated, treating frequency as a dependent count variable. Time, cubic time and quadratic time were added to the model as predictor variables. Each dyad was allocated to a trajectory group in each model.

The best fitting model was determined using the BIC values, the interpretability of the given trajectories, and the PGMPs of dyads. Table 5.37 shows the BIC values for the 1-6 class models. Figure 5.52 shows a plot of the BIC values.

Table 5.37 BIC values for 1-6 class frequency models

Model	BIC
1-Class	415.5132
2-Class	388.9165
3-Class	394.633
4-Class	399.1195
5-Class	407.6567
6-Class	422.6724

Figure 5.52 BIC values for 1-6 class frequency models



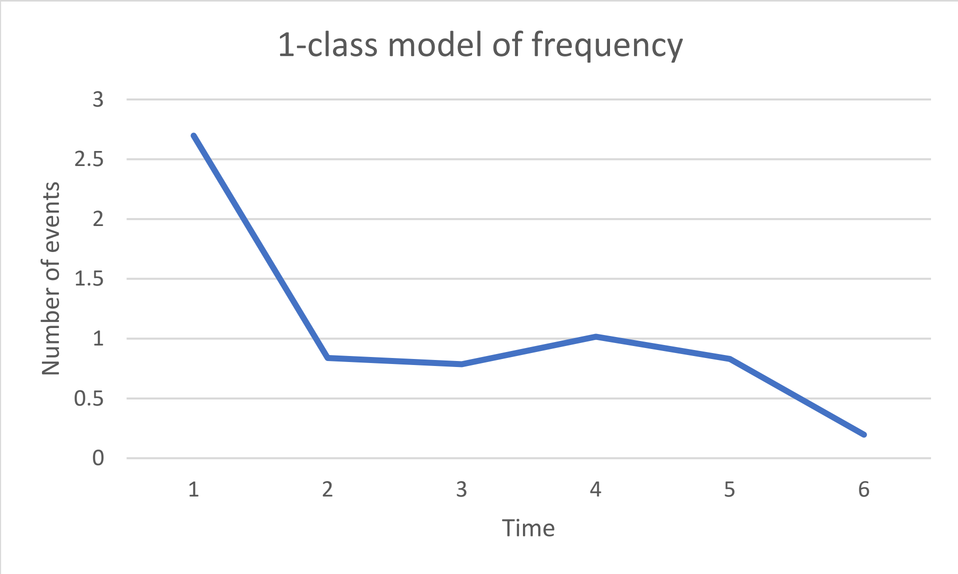
The 2-class model had the greatest reduction on the BIC value, indicating the best fitting model. The estimated values for each model were plotted to give the shapes of the estimated trajectories. Posterior group-membership probabilities (PGMPs) were assessed using Nagin's (2005) 0.7 threshold. The percentage of dyads with had a PGMP of 0.7 or above was computed for each model. As an additional class is added to each model, some dyads were reallocated to a new class. The reclassification of dyads was examined through crosstabs of dyad classification in each model with two or more classes, to better understand the contribution of individual dyads to the trajectory shapes.

5.2.3.4.1. 1-class frequency model

The 1-class frequency model gives the estimated values of frequency at each time-point for the average dyad.

The trajectory shows an overall decreasing frequency. The trajectory has an average estimate of between 2 – 3 recorded events in the first six months (time 1) that decreases to less than one event by the 6-12 month time-point (time 2). The average frequency remains around or just below one per six-month time-point between time 2 and time 5 (24 – 30 months), before decreasing to almost no recorded events by time 6 (30 – 36 months).

Figure 5.53 1-class frequency model



5.2.3.4.2. 2-class frequency model

Table 5.38 shows the class sizes for the 2-class model, 79% of dyads remained in class1, 21% were allocated to class2.

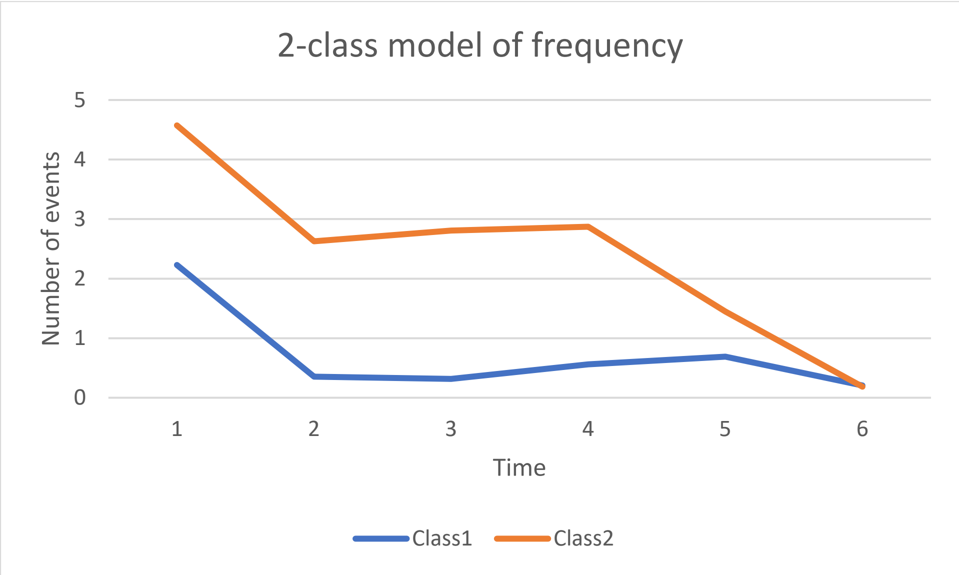
The 2-class model shown in Figure 5.54, shows two trajectories declining in frequency over time. Class1 is low frequency, starting with an average of just over two recorded events at time 1 to below one at time 2 and then remaining below one throughout the three-year period, with the lowest estimate at time 6. Class2 is higher frequency, with a first estimate of between 4 – 5 events at time 1 and decreasing to 2 – 3 at time 2. The frequency in class2 remains steady at around 3 events per six months until time 4, and then decreases sharply to an estimate of close to zero at time 6.

100% of dyads have a PGMP of 0.7 or above.

Table 5.38 Class sizes for 2-class frequency model

	Class1	**Class2**
Class Size	0.79	0.21

Figure 5.54 2-class frequency model



5.2.3.4.3. 3-class frequency model

Table 5.39 shows the class sizes for the 3-class model. 50% of dyads were allocated to class1, 39% were allocated to class2, and 11% were allocated to class3.

Figure 5.55 shows class1 is a low frequency trajectory that fluctuates in frequency over the three-year time-period. The average number of recorded events within a six-month time-point remains below two and decreases to almost zero events at time 6. Both class2 and class3 show declining trajectories. Class2 is a much lower frequency, starting with an estimate of just below three recorded events at time 1, declining to almost zero by time 3 and remaining very low for the remainder of the trajectory. Class3 has the highest estimated frequency, starting with an estimate of between 6 – 7 recorded events in the first time-point and steadily declining to just below one in the final time-point.

Table 5.39 shows the reallocation of dyads. In class1, 88% of dyads came from the previous class1, and 13% of dyads came from class2. In the class2, 91% of dyads came from class1, 9% from class2. In the new class3, all dyads came from class2.

77% of dyads have a PGMP of 0.7 or higher.

Table 5.39 Class sizes for 3-class frequency model

	Class1	Class2	Class3
Class Size	0.4975	0.3877	0.1147

Figure 5.55 3-class frequency model

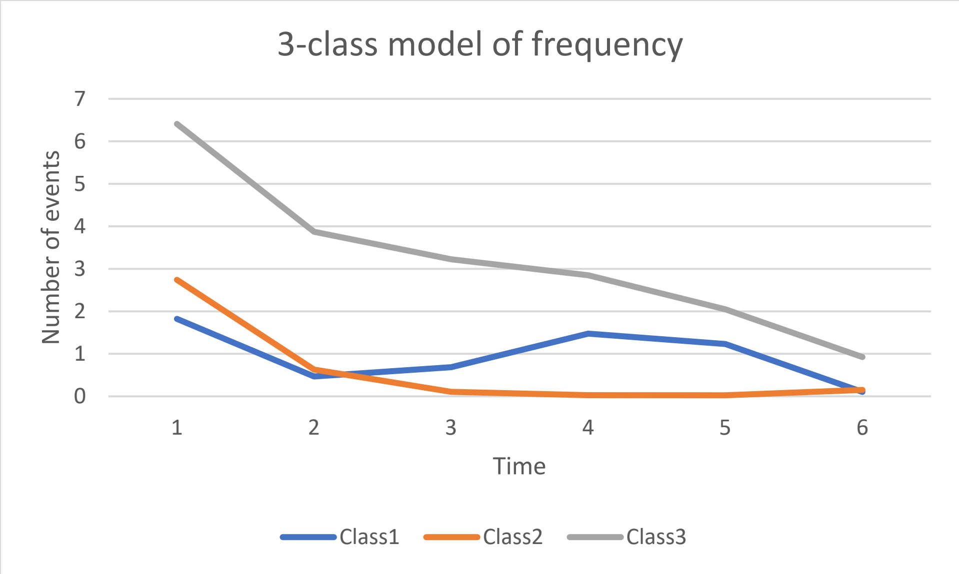


Table 5.40 Reallocation of dyads from 2-class to 3-class frequency model

	1-class classification	2-class classification
3-class classification	**Class1 (%)**	**Class2 (%)**
Class1	88	13
Class2	91	9
Class3	0	100

5.2.3.4.4. 4-class frequency model

Table 5.41 shows the class sizes for the 4-class model, 48% of dyads were allocated to class1, 33% to class2, 12% to class3, and 7% to class4.

Class1 and class2 are the lowest frequency trajectories. Class1 decreases from an estimate of around two at time 1 to almost zero by time 2, increasing slowly to one at time 5 and then decreasing again to almost zero at time 6. Class2 starts with an estimate of almost three at time 1 before declining to almost zero at time 3 and remaining close to zero for the remainder of the trajectory. Class3 shows a fluctuating trajectory, remaining around 1-2 events in the first two time-points, then increasing to almost four at time 5 and then declining steadily to almost zero in the final time-point. Class4 has the highest frequency, starting with an estimate of almost nine events at time 1 and steadily declining over time to almost zero by time 5.

Table 5.42 shows all dyads in class1 came from the previous class1, and all dyads in class2 came from the previous class2. In class3, two thirds (67%) of dyads came from class1, and 33% from the previous class3. In the new class4, all dyads came from the previous class3.

80% of dyads have a PGMP of 0.7 or above.

Table 5.41 Class sizes for 4-class frequency model

	Class1	Class2	Class3	Class4
Class Size	0.4754	0.328	0.1234	0.0733

Figure 5.56 4-class frequency model

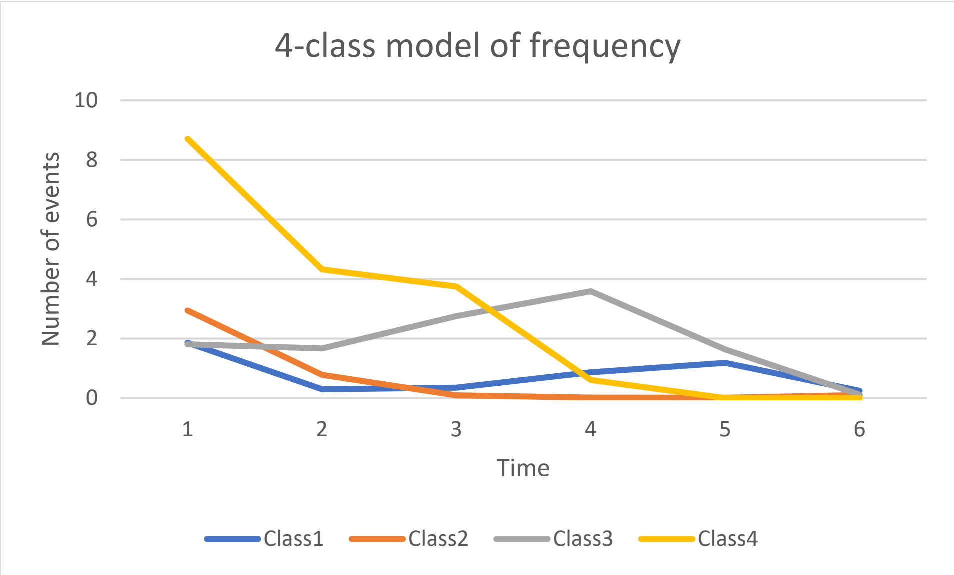


Table 5.42 Reallocation of dyads from 3-class to 4-class frequency model

			3-class classification
4-class classification	**Class1**	**Class2**	**Class3**
Class1	100	0	0
Class2	0	100	0
Class3	67	0	33
Class4	0	0	100

5.2.3.4.5. 5-class frequency model

Table 5.43 shows 33% of dyads were allocated to class1, 28% of dyads were allocated to class2, 28% of dyads were allocated to class3, 7% of dyads were allocated to class4, and 4% of dyads were allocated to class5.

Figure 5.57 shows class1 starts with an estimate of around three recorded events at time 1, decreasing to almost zero at time 3 and remaining low for the remainder of the trajectory. Class2 fluctuates, with an estimate of around two at time 1, decreasing to almost zero at time 2 before steadily increasing to almost three at time 4 and then decreasing again to almost zero at time 6. Class3 follows a similar fluctuating pattern as class2 though with a lower average frequency throughout the centre of the trajectory, maintaining an estimate of almost zero between time 2 and time 3 before slowly increasing to an estimate of one at time 5 and then decreasing again to almost zero at time 6. Class4 shows a steadily declining trajectory with a high estimate of over eight events at time 1, decreasing to almost zero by time 5. The new class 5 shows a different trajectory pattern that steadily increases over time from around two events at time 1 to four events between time 4, and then slowly decreasing to an estimate just below one at time 6.

70% of dyads have a PGMP of 0.7 or above.

Table 5.43 Class sizes for 5-class frequency model

	Class1	Class2	Class3	Class4	Class5
Class Size	0.3247	0.2809	0.2806	0.0713	0.0425

Figure 5.57 5-class frequency model

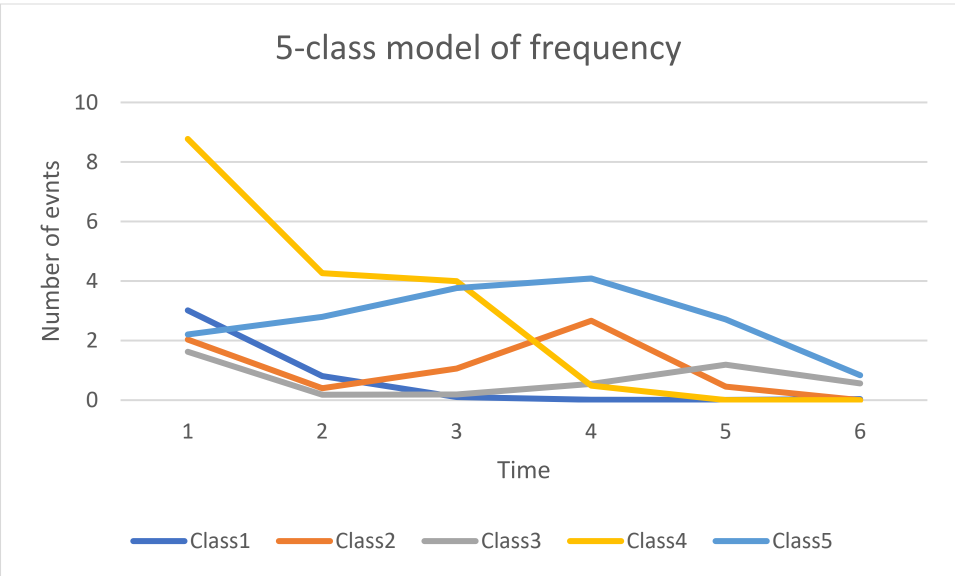


Table 5.44 Reallocation of dyads from 4-class to 5-class model

	4-class classification			
5-class classification	**Class1 (%)**	**Class2 (%)**	**Class3 (%)**	**Class4 (%)**
Class1	0	100	0	0
Class2	75	0	25	0
Class3	89	11	0	0
Class4	0	0	0	100
Class5	0	0	100	0

5.2.3.4.6. 6-class frequency model

Table 5.45 shows 28% of dyads were assigned to class1, 27% to class2, 21% to class3, 13% of dyads to class 4, 7% of dyads to class5, and 4% of dyads to class6.

Figure 5.58 shows that as more classes are added to the model, the trajectories are increasingly difficult to interpret. Class1 now remains around three events per six-month period for the first three time-points, before sharply increasing to almost nine events at time 5 and declining to just over two at time 6. Class2 remains low frequency with estimates below one for the first three time-points, before increasing to around four at time 5 after the first event. Class3 follows a similar pattern as class2 though has a sharper increase between time 4 and time 5. Class4 suggests a possible period of intermittency, starting with an estimate between 2-3 events at time 1, declining to almost zero time 2 and time 3, then increasing by time 6. Class5 shows a fluctuating trajectory, remaining below one in the first two time-points, increasing to just above one at time 3, decreasing to almost zero between time 4 and time 5 and increasing again at time 6. Class6 remains close to zero for most of the trajectory, with a small increase of almost one at time 3, and another increase at time 6 of almost one again.

Table 5.45 shows all dyads in class1 came from the previous class2. In class2, 64% of dyads came from class1 and 36% from class3. All dyads in class3 came from the previous class3. All dyads in class4 came from the previous class1. All dyads in class5 came from the previous class4. All dyads in the new class6 came from the previous class5.

63% of dyads have a PGMP of 0.7 or higher.

Table 5.45 Class sizes for 6-class frequency model

	Class1	Class2	Class3	Class4	Class5	Class6
Class Size	0.28	0.2727	0.2051	0.1326	0.0685	0.0411

Figure 5.58 6-class frequency model

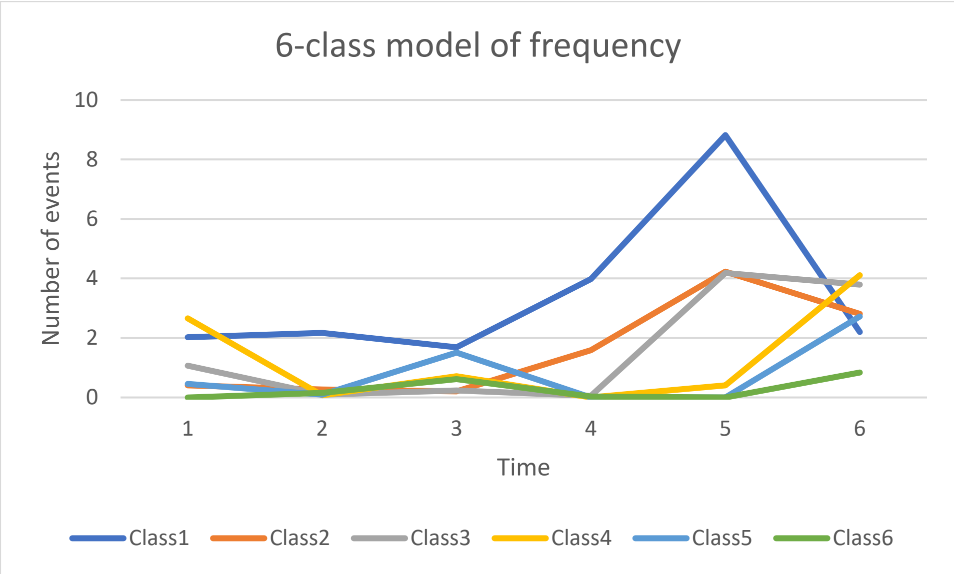


Table 5.46 Reallocation of dyads from 5-class to 6-class frequency model

					5-class classification
6-class classification	**Class1 (%)**	**Class2 (%)**	**Class3 (%)**	**Class4 (%)**	**Class5 (%)**
Class1	0	100	0	0	0
Class2	64	0	36	0	0
Class3	0	0	100	0	0
Class4	100	0	0	0	0
Class5	0	0	0	100	0
Class6	0	0	0	0	100

5.2.3.4.7. Summary of frequency trajectories

The 2-class model is determined to be the best fitting model. The 2-class model has the greatest reduction on the BIC value. All dyads in the 2-class model have a PGMP greater than Nagin's (2005) threshold of 0.7. The two trajectories show different and interpretable patterns of escalation. The first class class1 is the largest and accounts for 79% of dyads. Class1 is interpreted to be a declining low frequency trajectory. Class2 accounts for the remaining 21% of dyads and is interpreted as a declining high frequency trajectory. The number and shapes of the trajectories identified in the frequency analysis differ to those in the descriptive analysis of frequency and severity trajectories.

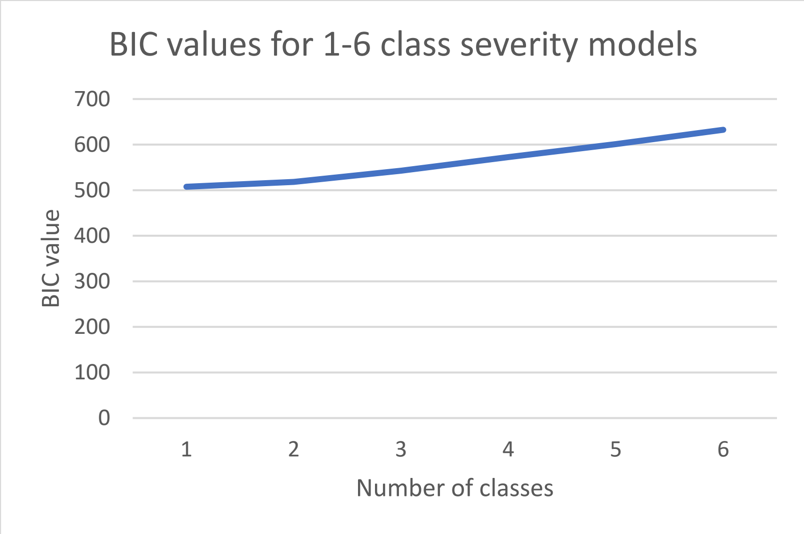
5.2.3.5. Latent trajectories of severity

Latent trajectory models were fitted to the same subset of dyads as the frequency analysis. Severity was measured using severity scores adapted from Heeks et al's (2018) Cost of Crime Harm Index. Each event experienced by a dyad represented one time-point. The most events experienced by a dyad was 18, thus 18 time-points were added to the data. As not all dyads experienced the same number of events, not all dyads contributed to all 18 time-points. Where a dyad did not contribute, the time was recorded as missing for that dyad. The severity subset was read into LatentGold to fit regression models. The time, quadratic time, and cubic time variables were added to the model as predictors. The dependent variable was severity. Severity was treated as an ordinal variable. Six models with between 1-6 classes were estimated. Table 5.47 shows the BIC values for the 1-6 class models. Figure 5.59 shows the change in BIC value as increasing with the addition of each class to the model.

Table 5.47 BIC values for 1-6 class trajectory severity models

Model	BIC
1-Class	507.5328
2-Class	518.0866
3-Class	542.9352
4-Class	572.603
5-Class	601.1096
6-Class	632.5227

Figure 5.59 BIC values for 1-6 class severity models

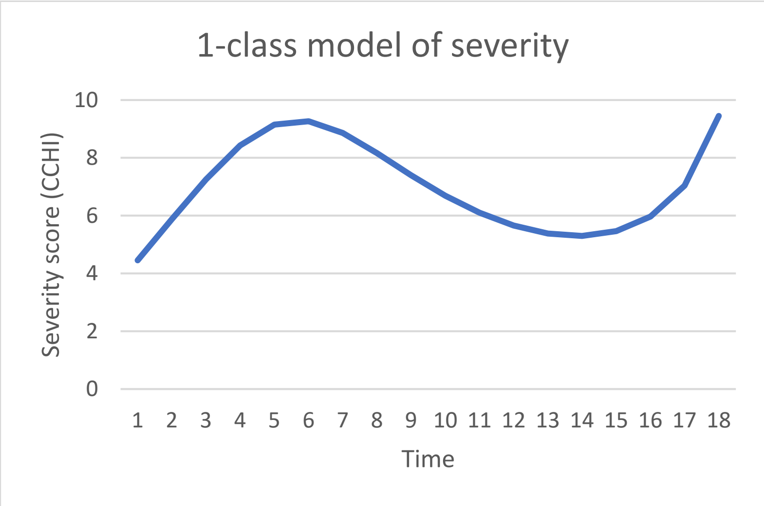


Unlike the frequency model, which demonstrates a reduction in the BIC when a second class is added to the model, the severity model shows that the BIC value increases as classes are added. The increase suggests that the fit is worse when the model assumes there is more than one trajectory. The best fitting model is therefore to assume there is only one trajectory.

5.2.3.5.1. 1-class severity model

The 1-class severity model gives the estimated severity score at each event for an average dyad. Figure 5.60 shows the trajectory fluctuates throughout the time-points, starting with an estimate of 4.5 at the first recorded event, increasing to around 9 at point 6, decreasing to just above 5 at point 14, before increasing in the final time-points. The trajectory is interpreted to represent the average trajectory of severity for dyads that came to the attention of the police more than once in a three-year time-period.

Figure 5.60 1-class severity model



5.2.3.5.2. Summary of severity trajectories

The BIC values indicated that the severity model worsened as classes were added to the model. The results thus indicate that the best fitting model to the data is one trajectory. This may indicate that the sample is too small to detect a pattern, and more data are needed to identify different severity trajectories. Alternatively, the results could indicate that in the cases that come to police attention, there is little variation in the pattern of severity over time between dyads. This would be an area of interest if this result suggested there is a particular trajectory of severity that comes to police attention. This is an area for further analysis with more data, and is beyond the scope of this thesis.

5.2.3.6. Testing for association between frequency and severity

The relationship between frequency and severity in the data was tested for significance using Pearson Chi-Squared tests. As the trajectory analysis revealed no identifiable trajectory groups in the severity model, any association between the trajectory pattern of frequency and severity could not be tested.

To examine for any relationship using a Pearson Chi-Squared test, the dyads were manually divided into groups of low to high frequency, and low to high severity. For the frequency groups, the number of events experienced by a dyad were aggregated into three categories of low (2-5), medium (6-9), and high (10+). For severity, the maximum severity score experienced by a dyad were aggregated into three categories, low (0 – 6.80), medium (6.81 – 16.10) and high (16.11+). The offence in the dataset that falls into the highest severity score category is rape. Offences in the medium severity category include other sexual offences, violence with injury, and theft of vehicle. Offences in the lowest severity category include violence without injury, burglary, criminal damage (excluding arson), theft from person and theft (other).

A crosstab gave the proportion of dyads in each frequency group that were in each maximum severity group, the chi-squared test estimated the significance of the association. Table 5.48 shows more than half (59%) of dyads in the lowest frequency group are also in the lowest maximum severity group, 41% are in the medium maximum severity group. None of the dyads in the lowest frequency group are in the high maximum severity group. From the medium frequency group, half (50%) of dyads are also in the medium maximum severity group, the remainder are split between low (25%) and high (25%). From the high frequency group, most dyads (83%) are in the medium severity group, 17% are in the high severity group. No dyads in the high frequency group are in the low severity group. A Pearson Chi-Squared test gives a p-value of 0.042, suggesting that there is a significant association at the 95% confidence level between the number of events experienced by a dyad and the maximum severity of events experienced by a dyad.

Table 5.48 Severity group classification of dyads in each frequency group

Frequency group	**Severity group**		
	Low (0 – 6.80) (%)	Medium (6.81 – 16.10) (%)	High (16.11+) (%)
Low (2-5)	59	41	0
Medium (6-9)	25	50	25
High (10+)	0	83	17

Significance: *

*P < 0.05; **P < 0.01; ***P <0.001

5.2.3.7. Summary

Escalation in police-recorded DVA was examined in four phases. The first phase used variables derived in the data to compare reported escalation in the first and last events for repeat dyads. Across all derived variables of severity, reported escalation was higher in the last recorded event than the first. The proportion of cases classified as medium and high-risk was also higher in the last event than the first event. These findings suggest that for at least some dyads, there was escalation in frequency and/or severity between the first and last recorded event, though this analysis could not account for fluctuation in frequency or severity between these events. Three hypotheses of escalation trajectories were then tested in the data: one trajectory (escalation), two trajectories (escalation, stable), and three trajectories (limited, low rate chronic, high rate chronic).

Trajectories of escalation were first observed through descriptive plots of DVA events by date and severity for all repeat dyads. Four patterns of escalation in frequency and severity were identified:

escalation, de-escalation, stability, fluctuation. The descriptive trajectories did not support the hypotheses that there are between one - three stable DVA trajectories. Two latent trajectory analyses then statistically modelled escalation trajectories. The frequency model indicated that two trajectories best fit the data. The first trajectory is a low-frequency declining trajectory, and the second a high-frequency declining trajectory. The severity model indicated that the best fitting model was only one trajectory. The severity trajectory is interpreted as representing the average pattern of severity for the dyads in the data. The severity trajectory fluctuates, increasing and decreasing over the course of the trajectory.

The two frequency trajectories do not support any of the hypotheses, as both show decline over time, rather than any patterns of increasing or stable frequency. The number and shape of the trajectories may be a product of the small sample of dyads included in this analysis. Looking specifically at the literature on DVA escalation in police data, the findings on frequency do not support those of Brimicombe (2016) who found no evidence of increasing severity, but found increases in frequency of calls to police prior to violent events. The findings also do not correspond to those of Barnham et al (2017) who found no evidence of increasing harm, though did find that frequency was progressively shorter as the number of events increased, indicating increasing frequency. The findings do not correspond to those of Bland and Ariel (2017) who found an increasing rate of frequency as the number of sequential events increased. Unlike Brimicombe or Barnham et al, Bland and Ariel did find some evidence of increasing severity, though specifically for a small subset of dyads that had the highest frequency. The severity trajectory found in this analysis does not show a straightforward direction of change over time, and instead demonstrates fluctuations throughout the trajectory. This fluctuation does not appear to be represented in the existing literature.

Looking at the relationship between frequency and severity, a Pearson's Chi-Squared test indicated a significant association between the number of events recorded for a dyad and the maximum severity score recorded for the dyad. This does not support the findings of Barnham et al (2017) or Bland and Ariel (2017), who found evidence to suggest the frequency of events did not have a significant effect on the harm or severity of the events.

5.2.4. Do trajectories correspond with typologies?

The trajectory analyses aimed to determine whether any distinct trajectory shapes could be identified and whether the number and shape of the trajectories supported hypotheses derived from the literature. The descriptive trajectory analyses found four trajectories: escalating, de-escalating, stable, and fluctuating. The latent trajectory analyses found two trajectories of frequency (low frequency declining, high frequency declining), and no evidence of more than one trajectory of severity (fluctuating).

The next step was to examine whether there were any characteristic differences between the identified trajectories. In the literature, Walby and Towers (2018) state that DVA escalates in frequency/severity when the victim lacks the economic resilience to escape the perpetrator. DVA is gendered, and the most frequent and severe forms of DVA are against women. Johnson suggests that intimate terrorism, the frequent, controlling, escalating form of DVA is predominantly males against female intimate partners, whilst common couple violence, the infrequent, low severity, not escalatory form of DVA is gender symmetrical. Bland and Ariel's (2017) analysis of DVA in police data found that in 'chronic' dyads, those with five or more recorded events in their sample, dyads were more likely to be unemployed, female victims. The data were examined to determine any characteristic differences between the dyads in each trajectory group, that support the arguments of the literature that the most severe and frequent forms of violence are by males against female intimate partners with less economic resources. The economic measure used was the employment status of the victim and perpetrator.

The characteristics were examined for the four-trajectory manual classification groups, and for the latent trajectories of frequency. As no distinguishable trajectories for severity were identified, there trajectories to compare. Instead, the characteristics for the repeat subset of victims included in the frequency and severity trajectory analysis were examined, to look at the how the overall group characteristics compare to those of the individual frequency trajectories.

5.2.4.1. Characteristics of descriptive trajectories

Table 5.49 gives victim, perpetrator, and dyad characteristics for the dyads in the four descriptive trajectories. Some of the same victims appearing in multiple dyads affect the figures. Females accounted for the majority of victims across all groups, the highest percentage in the fluctuating trajectory (91%). No victims in the fluctuation group were employed in the first event. The escalation group had the highest proportion of victims employed in the first event, though this was still less than half (47%). No victims were employed in their first event in the fluctuating group. Table 5.49 shows the proportion of victims that identified mental health, financial, alcohol and substance use issues at some point in the trajectory.

Males accounted for the majority of perpetrators across all groups. In the fluctuation group, all perpetrators were male. The lowest employment rate was in the stable group, with 9% of perpetrators employed in the first event. The table also shows the percentage of perpetrators in each group with known previous DA referrals involving a different victim, known previous convictions, known warning markers for violence and/or weapons, mental health, financial, alcohol and substance use issues.

IPV accounted for the majority of dyads in each group, all dyads in the de-escalation and fluctuation groups were intimate partners. For frequency, all dyads in the stable trajectory and more than three quarters (78%) in the de-escalation trajectory were in the low frequency group with between 2-5 events. Almost one quarter of escalation dyads were in the medium frequency group with between 6-9 events, and 12% were in the high frequency group with 10+ events. In the fluctuation trajectory, less than a fifth (18%) were in the low frequency group, more than half (55%) were in the medium frequency group, and more than a quarter (27%) were in the high frequency group. For severity, all dyads in the stable trajectory were in the lowest maximum severity group. No dyads in the de-escalation trajectory were in the high maximum severity group. Both the escalation and fluctuation trajectory group had a small percentage (8%/9%) of dyads in the high severity group.

Table 5.49 Characteristics of four descriptive trajectories

Factor	One: Escalation (%)	Two: De-escalation	Three: Stability	Four: Fluctuation
Victim				
Female	69	78	80	91
Male	31	22	20	9
Employed (first event)	47	44	7	0
Mental health issues	44	67	27	82
Financial issues	44	33	13	18
Alcohol problems	31	33	33	46
Substance use problems	44	11	13	27
Perpetrator				
Female	19	11	27	0
Male	81	89	73	100
Employed	31	22	9	27
Known DV perpetrator	38	56	53	64
Previous convictions (first event)	69	44	27	64
Warning marker for violence and/or weapons (first event)	25	33	40	27
Mental health issues	44	44	27	46
Financial issues	38	44	7	18
Alcohol problems	50	11	33	55
Substance use problems	50	56	33	55
Dyad				
Intimate partner violence	81	100	80	100
Family violence	19	0	20	0
2-5 events	65	78	100	18
6-9 events	24	22	0	55
10+ events	12	0	0	27
Low maximum severity	47	56	100	9
Medium maximum severity	45	44	0	82
High maximum severity	8	0	0	9

Table 5.50 shows no significant association found between victim sex, perpetrator sex, perpetrator employment status, or relationship with the descriptive trajectory classification. The relationship variable in the table includes all relationship options (partner/ex; son/daughter; brother/sister; parent; grandparent; other). There was a significant association between victim sex and trajectory classification. The test is limited as it does not give information on the size or direction of the relationship between victim sex and trajectory shape. There was also significant association between the number of events experienced by a dyad, the maximum severity experienced by a dyad, and their trajectory classification.

Table 5.50 Significance of characteristics in descriptive trajectories

Characteristic	X-squared	Df	Significance
Victim			
Sex	1.923	3	NS
Employment status	12.232	3	**
Perpetrator			
Sex	3.670	3	NS
Employment status	4.754	6	NS
Dyad			
Relationship	6.375	6	NS
Number of events	20.766	6	**
Maximum event severity	30.62	6	***

5.2.4.2. Characteristics of frequency trajectories

Most dyads (n=24) were allocated to the first trajectory (class 1), with the remaining six dyads allocated to the second trajectory (class 2).

Table 5.51 shows that in the high frequency dyads (class 2), most victims were female (83%) and the majority of perpetrators male (83%). Only one victim (17%) was employed in their first event. Most had identified mental health issues (83%), half had problems with alcohol (50%) and two-thirds (67%) had problems with substance misuse. Across all dyads and each trajectory group, a third (33%) of perpetrators were employed at the first event. In the high frequency group, two perpetrators (33%) were known to be a previous DVA perpetrator at the first event for the dyad. All perpetrators in the high frequency group (100%) had at least one known conviction for any offence in the first event for the dyad. All perpetrators had identified mental health issues, half (50%) had problems with alcohol and five out of six (83%) had issues with substance misuse. Across all dyads, most were intimate partner (90%), in the highest frequency group this was all dyads (100%). All dyads in the high frequency trajectory had at least six recorded events. All dyads that had events in the highest severity scores category (16.11+) were in the high frequency group.

Table 5.51 Victim, perpetrator, and dyad characteristics of the frequency trajectories

Factor	Class one: low frequency decline (%)	Class two: high frequency decline (%)	All dyads (%)
Victims			
Female	67	83	60
Male	33	17	30
Employed (first event)	29	17	27
Mental health issues	58	83	63
Financial issues	38	33	37
Alcohol problems	17	50	23
Substance use problems	13	67	23
Perpetrators			
Female	17	17	17
Male	83	83	83
Employed	33	33	33
Known DV perpetrator	67	33	60
Previous convictions (first event)	63	100	70
Warning marker for violence and/or weapons (first event)	38	50	40
Mental health issues	38	100	50
Financial issues	38	33	37
Alcohol problems	33	50	37
Substance use problems	42	83	50
Dyads			
Intimate partner violence	88	100	90

Family violence	13	0	10
2-5 events	75	0	60
6-9 events	17	33	20
10+ events	8	67	20
Low maximum severity	46	0	37
Medium maximum severity	54	67	57
High maximum severity	0	33	7

Table 5.52 shows no significance found between victim or perpetrator sex, victim or perpetrator employment status, or dyad relationship on the frequency classification. There was a significant association between the number of events experienced by a dyad and the maximum event severity experienced with frequency classification. The test is limited as it does not give any information on the size or direction of the relationship between these variables and trajectory classification.

Table 5.52 Significance of characteristics in frequency trajectories

Characteristic	X-squared	Df	Significance
Victim			
Sex	0.635	1	NS
Employment status	0.384	1	NS
Perpetrator			
Sex	0	1	NS
Employment status	0.087	1	NS
Dyad			
Relationship (Intimate or family)	0.33	1	NS
Number of events	13.333	2	***
Maximum event severity	10.882	2	**

5.2.4.3. Summary

The characteristics of trajectory groups were observed to compare to the characteristics of existing DVA theories, namely Johnson's dichotomous typology and Walby and Towers' domestic violent crime. Both suggest that the most frequent and severe repetitions of DVA are by men towards women, and particularly women with lower socioeconomic status.

In the descriptive trajectories, the highest percentage of female victims and the lowest employment rate were in the fluctuating trajectory. In the fluctuating trajectory, all perpetrators were males and all IPV. Over a quarter of dyads in the fluctuating trajectory were in the highest frequency group with 10 or more events, and most were in the mid or high severity group. In the escalation trajectory, the percentage of female victims was fewer than in the fluctuation trajectory, though females still accounted for the majority of victims. The employment rate in the escalation trajectory was the highest across the descriptive trajectories, though still less than half of victims were employed. Most perpetrators were male and most dyads were intimate partners. The descriptive trajectories suggest some characteristic differences between trajectories, with the most frequent and severe DVA being perpetrated by males against females and the unemployed, and between intimate partners.

The frequency trajectories identified in the latent trajectory analysis were compared to the characteristics of all dyads in the subset. Though based on a small number of dyads (6 out of 30), the higher frequency trajectory had the highest percentage (83%) of female victims and the lowest level of victim employment (17%). The same percentage of male perpetrators appeared across all dyads and within each trajectory (83%). All dyads in the higher frequency trajectory were intimate partner. Although based on a small number of dyads, these proportions appear to support the theories of Johnson and Walby and Towers that the most frequent DVA is by males against females, particularly against victims with lower socioeconomic status. Although lower than the higher frequency group, female victims and male perpetrators were the majority across dyads, and employment rate was low for all dyads in the data (27% of victims and 33% of perpetrators were recorded as employed in the first recorded event). However, unlike Johnson or Walby and Towers suggest, the high frequency trajectory did not show an escalatory pattern, and instead the trajectory analysis suggested that overall frequency declined over time. Although, as this is a specific subset of police data, these trajectories may indicate only changes in the reporting and recording of repeat DVA to this police force over a specific period, and the data have no information on whether this parallels the true trajectory of DVA for each dyad.

Overall, the analyses indicate that there may be differing patterns of escalation for dyads in the data that repeatedly came to the attention of police, particularly in relation to frequency. Further analysis with a larger sample of data should investigate these patterns of fluctuations, and characteristics, events or interventions that occur at time-points of increase and decrease in frequency and severity.

The latent trajectory analysis suggested that no more than one fluctuating trajectory of severity should be modelled. This may suggest that there was not enough data to identify multiple trajectories, or alternatively, this may indicate that the same pattern of severity was represented by the dyads in the sample. For frequency, the analysis suggested two trajectories that decline in frequency over time. Although the results do not correspond to theories of escalating frequency the trajectories do support the theories that the most frequent DVA is by males against female intimate partners, particularly victims with lower socioeconomic status. These associations were not found to be significant. This may be due to the small sample size and warrants further analysis with more data, though this is beyond the scope of this thesis.

5.3. Is there any association between police action and DVA repetition?

The next stage of analysis was to determine whether any associations between the available measures of police action and repetition could be identified in the data. Existing literature has examined aspects of the police response in its ability to predict or prevent further DVA, such as risk assessment (Robinson and Howarth, 2012; Almond et al, 2017), arrest (Sherman et al, 1992), and multi-agency responses (Robinson, 2006). This section looks for any relationship between measures of police action and DVA repetition through three sub-questions tested in separate analyses. The first question looked at the types of actions taken by the police in response to DVA, the second assessed for any association between police action and the frequency of DVA, and the third assessed for associations between police action and the severity of DVA. External cases (n=5), that is cases reported to other police forces or agencies, were excluded from all analyses.

5.3.1. What actions do the police take?

As discussed in the Literature Review, there are multiple options open to the police when responding to DVA. Not all actions and disposals were available in the data. Of the available variables, cross tabulations gave the percentage of police responses in each event type. Pearson Chi-Squared tests determined whether the associations between the response types and the event types in the data were significant. The response percentages are given by event type for non-crimed events and crimed events.

5.3.1.1. Response grading

Table 5.53 gives the percentage of all events and each ‘non-crimed’ event type that were allocated each response grade. The most common (44%) grading given was an emergency response. Less than a third (30%) were allocated a priority response, less than a quarter (21%) a planned response, and

5% were resolved over the telephone in FCR. A chi-squared test gave a p-value of 0.091, therefore no significant association was identified.

Table 5.53 Priority response grading, by non-crimed event

Non-crimed event type	Number of events	Priority response grading			
		Emergency (%)	Priority (%)	Planned (%)	Telephone resolution (%)
(Crimed event)	161	42	30	24	3
Rape	1	100	0	0	0
Sexual offences	0	:	:	:	:
Assault with injury	2	0	0	50	50
Assault without injury	5	40	20	40	0
Theft	3	67	0	33	0
Criminal damage	1	100	0	0	0
Breach	15	27	27	27	20
Stalking	0	:	:	:	:
Harassment	8	25	25	38	13
Threats	21	57	24	14	5
Verbal altercation	84	45	37	14	4
Other	15	53	13	13	20
Total	316	44	30	21	5

Significance: NS

Table 5.54 gives the percentage of each crimed offence type that were allocated each response. More than two fifths (42%) of events were allocated an emergency response, less than a third (30%) were allocated a priority response, just under a quarter (24%) a planned response, and 3% were resolved over the telephone in FCR. A chi-squared test gave a p-value of 0.320, therefore no significant association was identified.

Table 5.54 Priority response grading, by offence

Offence subclass	Number of events	Priority response grading			
		Emergency (%)	Priority (%)	Planned (%)	Telephone resolution (%)
Violence with injury	58	48	31	21	0
Violence without injury	49	45	33	16	6
Rape	1	100	0	0	0
Stalking /Harassment	21	10	38	48	5
Public Order	3	67	33	0	0
Criminal Damage	20	45	25	25	5
Burglary – Residential	4	50	25	25	0
Theft from the Person	1	100	0	0	0
Other Theft	4	25	0	75	0
Total	161	42	30	24	3

Significance: NS

5.3.1.2. Risk classification

The percentage of events where the police conducted a risk assessment and the percentage of events given each risk classification were examined. Table 5.55 shows that DASH was completed for over half (59%) of events. For more than a third (36%) of events, DASH was recorded as refused by the victim. A small percentage (4%) were recorded as not completed. Not completed cases included events where frontline officers did not attend the scene, and events where two DVA crimes have been recorded from the same incident with two victims though only one DASH is completed thus the second event is recorded as not completed. These findings may support previous research that DASH are often missing or incomplete (Robinson et al, 2016). Data were missing for 15% of events as these events occurred prior to the DASH system being introduced across the force in March 2009.

Table 5.55 Percentage of events where DASH was completed

DASH completed	Percentage (%)
Yes	59
No – refused by the victim	36
No – not completed	4

Data were missing for 15% of events, these cases were excluded

Table 5.56 gives the percentage of events that were allocated each risk classification. Just over half (52%) were allocated standard-risk, more than a quarter (28%) medium-risk, and less than a fifth (19%) were allocated high-risk. A chi-squared test gave a p-value of <0.001, indicating a highly significant association between the type of non-crimed event and the risk classification given to the event.

Table 5.56 Risk classification, by non-crimed event

Non-crimed event	**Risk classification**		
	Standard (%)	**Medium (%)**	**High (%)**
(Crimed event)	33	36	31
Rape	0	0	100
Sexual offences	:	:	:
Assault with injury	0	50	50
Assault without injury	80	20	0
Theft	100	0	0
Criminal damage	0	0	100
Breach	20	47	33
Stalking	:	:	:
Harassment	75	25	0%
Threats	67	24	10
Verbal altercation	81	18	1
Other	87	13	0
Total	52	28	19

Significance: ****

Table 5.69 shows the risk classification given by crimed offence type. Just less than a third (33%) were classified as standard-risk, 36% as medium-risk, and 31% as high-risk. A chi-squared test gave a p-value of 0.314, therefore no significant association was found.

Table 5.57 Risk classification, by offence

Offence subclass		**Risk classification**	
	Standard (%)	**Medium (%)**	**High (%)**
Violence with injury	27	36	36
Violence without injury	43	31	27
Rape	:	:	:
Stalking/Harassment	14	52	33
Public Order	67	33	0
Criminal Damage	43	24	33
Burglary – Residential	25	75	0
Theft from the Person	0	100	0
Other Theft	25	25	50
Total	33	36	31

Significance: NS

5.3.1.3. Arrest

Table 5.58 gives the percentage of all events and each non-crimed event type that led to an arrest of the perpetrator. Just less than a third (33%) led to an arrest. A chi-squared test gave a p-value of <0.001, indicating a highly significant association between the type of non-crimed event and arrest.

Table 5.58 Perpetrator arrest, by non-crimed event

Non-crimed event type	Number of events	Percentage of events where the perpetrator was arrested (%)
(Crimed event)	161	46
Rape	1	50
Sexual offences	0	:
Assault with injury	2	100
Assault without injury	5	40
Theft	3	33
Criminal damage	1	100
Breach	15	53
Stalking	0	:
Harassment	8	0
Threats	21	24
Verbal altercation	84	8
Other	15	13
Total	316	33

Significance: ***

Table 5.59 gives the percentage of each crimed offence type that led to an arrest of the perpetrator. In total, just under half (46%) of all crimed DVA events led to an arrest of the perpetrator. A chi-squared test gave a p-value of 0.222, therefore no significant association was found.

Table 5.59 Arrest of perpetrator, by crimed offence

Offence subclass	Number of events	Percentage of events where the perpetrator was arrested (%)
Violence with injury	58	60
Violence without injury	49	39
Rape	1	0
Stalking/Harassment	21	33
Public Order	3	33
Criminal Damage	20	50
Burglary – Residential	4	25
Theft from the Person	1	0
Other Theft	4	25
Total	161	46

Significance: NS

5.3.1.4. Referral to another agency

Table 5.60 gives the percentage of all events and each non-crimed event type that were referred to another agency/organisation. In total, 62% of all events were referred /shared with another agency/organisation. A chi-squared test gave a p-value of <0.001, indicating a highly significant association between the event type and referral.

Table 5.60 Referral to another agency, by non-crimed event

Non-crimed event type	Percentage of events were referred to another agency (%)
(Crimed event)	73
Rape	100
Sexual offences	:
Assault with injury	100
Assault without injury	60
Theft	67
Criminal damage	100
Breach	80
Stalking	:
Harassment	38
Threats	52
Verbal altercation	42
Other	47
Total	**62**

Significance: ****

Table 5.61 gives the percentage of each crimed offence that were referred to another agency. Just under three quarters of crimed offences were referred to another agency or organisation. A chi-squared test gave a p-value of 0.461, therefore no significant association was found.

Table 5.61 Referral to another agency, by offence

Offence subclass	Percentage of events that were referred to another agency (%)
Violence with injury	70
Violence without injury	75
Rape	0
Stalking/Harassment	86
Public Order	33
Criminal Damage	68
Burglary – Residential	75
Theft from the Person	100
Other Theft	75
Total	73

Significance: NS

5.3.1.5. *Police identified outcome*

For every crimed offence, there was a police identified outcome. Table 5.62 gives the percentage of each offence subclass recorded with each outcome. The most common outcome, accounting for over half (62%) of all offences, was no further action (NFA). This is followed by court disposal, for 13% of crimed offences. A chi-squared test gave a p-value of <0.01, indicating a significant association between the offence subclass and the police identified outcome.

Table 5.62 Police identified outcome, by offence class

Offence subclass	Number of cases	Undetected (%)	Positive outcome (%)	Cancelled (%)	Prosecution not possible (%)	Closed (%)	Crime under active investigation (%)	Court disposal (%)	Police disposal (%)	No further action (%)
Violence with injury	58	10	7	2	2	25	0	14	2	62
Violence without injury	49	2	4	2	0	6	2	14	0	69
Rape	1	0	0	0	0	100	0	0	0	0
Stalking /Harassment	21	9	5	0	0	10	0	10	0	67
Public Order	3	0	33	0	0	0	0	0	0	67
Criminal Damage	22	5	14	0	0	9	0	18	9	46

Burglary – Residential	4	0	0	0	0	50	0	0	0	50
Theft from the Person	1	0	0	0	0	100	0	0	0	0
Other Theft	4	0	0	0	0	0	25	0	0	75
Total	163	6	7	1	1	7	1	13	2	62

Significance: **

Table 5.63 gives the percentage of each police recorded crime status within the crimes that resulted in NFA. The most common status was victim based evidential difficulties (58%).

Table 5.63 Recorded crime status of crimes that resulted in NFA

Police recorded crime status	Percentage of NFA crimes (%)
Evidential difficulties victim based - named suspect identified	58
Evidential difficulties named suspect identified	30
Named suspect - further investigation not in public interest	7
Evidential difficulties victim based - named suspect not identified	3
Prosecution time limit expired	1
Other agency delegations	1

5.3.1.6. Summary

Of all non-crimed and crimed events, 44% were graded as an emergency by the FCR, 52% were then graded as standard-risk in DASH, 33% of events led to the arrest of the perpetrator, and 62% of events were referred by the police to another agency or organisation. Of all crimed offences, which here account for 52% of all events, 62% were recorded with NFA. Chi-squared tests give some indication of significance between event types and police response, though the chi-square test cannot give the size or direction of the relationship and does not imply a causal link.

5.3.2. Is there any association between the type of action taken and the frequency of repeat DVA?

The association between police action and DVA repetition first looked at frequency. Two measures of frequency were examined. The analyses first assessed the relationship between police action and the two frequency trajectory groups identified in the latent trajectory analysis. The analysis then modelled the annual rate of events experienced by a dyad as predicted by police actions and individual factors in a Poisson log-linear regression model.

5.3.2.1. Arrest, referral, and frequency trajectory membership

Cross-tabulations and Pearson Chi-Squared tests assessed the significance of the association between variables of police action and dyad membership to the two frequency trajectories. The frequency subset of 30 dyads was used. The included police action variables were perpetrator arrest and referral to another agency, by type of agency. Table 5.64 shows the percentage of dyads in each trajectory group that were arrested or referred to an agency at least once. The number of times a dyad received an action was not accounted for. For each action, the percentage of dyads that received the response is higher in the high frequency group than in the low frequency group. A Pearson's Chi-Square tested for an association between receiving each of the actions and the trajectory classification. Arrest, referral to probation; health; mental health; CSC; CFW; ASC; Other and MARAC all showed significant associations with frequency trajectory classification. The test does not provide the size or direction of this relationship.

Table 5.64 Percentage of arrests and referrals by frequency trajectory

Response	Class one: low frequency decline (%)	Class two: high frequency decline (%)	Significance
Arrest	50	100	*
Referral to agency	92	100	NS
Probation	54	100	*
IDVA	91	100	NS
Health	50	100	*
Mental health	0	17	*
CSC	46	100	*
CFW	4	33	*
ASC	0	33	**
Education	17	50	NS
Substance misuse	17	17	NS
Other	17	67	*
MARAC	9	67	**

5.3.2.2. Frequency regression model

To investigate the direction and size of any association between individual factors, police action and the frequency of DVA experienced by a dyad, the associations were tested in a regression. The dependent variable was the frequency rate, predicted by each of the explanatory variables shown in Table 5.65. Rather than looking at frequency as the shape of change over time, the regression analysis was interested in whether any factors had an effect on the average number of events experienced by a dyad. The frequency rate was calculated as the average number of events recorded against a dyad per year, using a two-year average. A two-year average was chosen to increase the representativeness of the estimate for the dyad compared to taking the number of recorded events in the first year, without omitting even further dyads from the analysis, which would be required if the average was increased to three or more years. The inclusion criteria for the regression analysis were all dyads with two or more events recorded within a two-year period (n=51). To get a two-year average for each dyad, only dyads that were able to have a full two-year trajectory in the data were included. As the final date of the study period is 16th November 2018, only dyads whose first recorded event was on or prior to 16th November 2016 were included. This omitted 12 dyads. A further five dyads were omitted due to having a gap of more than two years between the first and second recorded event. This left a sample of **34** dyads.

As the dependent variable is a rate, a Poisson log-linear model was estimated. All explanatory variables were tested for significance using a forward selection procedure. Table 5.65 shows the explanatory variables tested in the frequency, and later in the severity regression models. Table 5.66 shows the dependent variables used in the frequency and severity regression models.

Table 5.65 Explanatory variables tested in frequency and severity regression models

Variable	Description
Sex of victim	Police identified sex of victim
Sex of perpetrator	Police identified sex of perpetrator
Relationship	Relationship between victim and perpetrator
Response (first)	Police graded response priority given to the first DVA event relating to the dyad
Risk level (first)	Police risk classification given to the first DVA event relating to the dyad
Crime status (first)	Police crime status of first DVA event relating to the dyad. Excludes non-crimed events.
Arrest	Has perpetrator ever been arrested for any of the DVA events between the dyad (Y/N)
Charge	Has perpetrator ever been charged for any of the DVA events between the dyad (Y/N)
Referral	Has dyad ever been referred to another agency or organisation for any DVA events (Y/N)
IDVA	Has victim ever been referred to an IDVA for any DVA events (Y/N)
Probation	Has dyad ever been referred to probation services for any DVA events (Y/N)
Health	Has dyad ever been referred to health services for any DVA events (Y/N)
Mental health	Has dyad ever been referred to mental health services for any DVA events (Y/N)
Substance use	Has dyad ever been referred to substance use services for any DVA events (Y/N)
Education	Has dyad ever been referred to education services for any DVA events (Y/N)
CFW	Has dyad ever been referred to Child and Family Wellbeing for any DVA events (Y/N)
CSC	Has dyad ever been referred to CSC for any DVA events (Y/N)
ASC	Has dyad ever been referred to ASC for any DVA events (Y/N)
Other referral	Has dyad ever been referred to any other agency or organisation for any DVA events (Y/N)

Table 5.66 Dependent variables tested in regression models to predict frequency and severity of DVA in dyads

Variable	Description
Yearly rate	Estimated average number of events recorded per year per dyad, based on the first two years of a dyad trajectory
Mean severity score	The mean of all severity scores for each recorded event for each dyad in the first two years of a dyad trajectory. Scores were adapted from the Costs of Crime Harm Index (Heeks et al, 2018).

Table 5.67 shows the final frequency model. When all explanatory variables were tested, the final model suggested one variable, whether the dyad had been referred to MARAC at any point, had the most significant effect on dyad frequency rate. None of the remaining explanatory variables appeared significant when placed in a model with the MARAC explanatory variable. The results suggest that when all other explanatory variables are held constant, having at least one referral to MARAC indicates that a dyad will on average have 0.84 more recorded events per year, than a dyad with no MARAC referrals. The MARAC variable does not distinguish at which event the dyad was referred, or how many times the dyad was referred. The significance therefore does not suggest that a referral to MARAC led to a higher rate of events per year. The relationship may suggest that a referral to MARAC was linked to an increased frequency rate per year; or that dyads who were referred to MARAC had higher average frequency rates.

A goodness-of-fit test was performed looking at the residual deviance, the difference between the deviance of the fitted model and the maximum deviance of the ideal model. A Pearson chi-square test found that the difference between the model and the ideal model was not significant with a p-value >0.05, and therefore the model was deemed to be a good fit to the data.

Table 5.67 Final model of significant predictors on the number of DVA events per dyad

Predictor	Estimate	Standard Error	p-value	Significance
Intercept	0.6330	0.1330	<0.001	***
At least one referral to MARAC	0.8429	0.2736	<0.01	**

5.3.2.3. Summary

The relationships between police actions and frequency were examined in two phases. The first was tests for significance using Pearson chi-square tests between selected police actions and the frequency trajectories identified in the latent trajectory analysis. These individual tests of significance suggested that multiple variables had a significant association with the frequency trajectory classification: arrest, referral to probation; health; mental health; CSC; CFW; ASC; Other; and MARAC. The tests do not provide the size or the direction of the relationship between the action and the trajectory group, however the percentage of dyads experiencing the action is higher in the high frequency trajectory for all actions. It is therefore indicative that dyads who have experienced these actions are more likely to be in the high frequency trajectory classification.

The second phase tested the effect of more police actions, alongside individual factors, on the frequency rate of events per year for repeat dyads in a Poisson log-linear regression model. Of all the variables tested, the final model indicated that at least one referral to MARAC had the most significant association with a high DVA frequency rate.

In both analyses, the number of times the action took place nor the point in the trajectory in which it took place are accounted for. The estimates therefore only indicate that there is an association between these measures of police action and frequency, they do not determine whether frequency increased prior to or following the action. The time of action in the trajectory could derive different implications for the use of the action, thus this is an area for further analysis.

5.3.3. Is there any association between the type of police action taken and the severity of repeat DVA?

As no distinct trajectories were identified for severity in the latent trajectory analysis, this analysis of police action and severity was conducted in one phase.

5.3.3.1. Severity regression model

In the severity regression model, the same subset of dyads was analysed as the frequency regression. The dependent variable was the mean severity score of events experienced by the dyad within the two-year period. The Costs of Crime Harm Index (adapted from Heeks et al (2018)) was used to measure severity. The mean was chosen as the measure of severity to give an average severity score per dyad in the first two years of their trajectory, and to be consistent with the frequency regression model, which took the average frequency rate over the two-year trajectory period. The mean severity score was treated as a continuous variable. A linear regression model was fitted, assuming a normal distribution of the dependent variable. An alternative method considered was to take the maximum severity score experienced by a dyad, treating the maximum severity score as an ordinal variable in an ordinal logistic regression. A linear regression of the mean severity score was chosen to have an average over two-years that was more comparable to the frequency regression.

The severity variable was checked for the normal distribution assumption using a series of tests. These tests included a histogram and density curve, a QQ plot and a Shapiro-Wilk test (Karadimitriou, n.d.). Both graphical tests indicated that the severity variable did not follow a normal distribution. The Shapiro-Wilk test gave a p-value above 0.05, indicating that the variable did not follow a normal distribution. Both graphical tests indicated that the frequency variable did not follow a normal distribution. The Shapiro-Wilk test gave a p-value above 0.05, indicating that the variable did not follow a normal distribution. There are several approaches to dealing with the non-normality of the response variable such as variable transformations, or non-parametric tests (Pek et al, 2018). It was felt that the effects of transforming the response variable would be minimal to the interpretation of the results, and thus beyond the scope of this analysis. Future analysis may consider using alternative approaches to the non-normality of the response variable, or use data of a much larger sample size that has more allowance for breaches of the normality assumption.

Table 5.69 shows the final severity model. Three variables had a significant effect on the mean severity: the response grade allocated in the first event; at least one arrest of the perpetrator; and whether the first event was crimed. The response grade is the level of priority allocated to the call (1 = Emergency; 2 = Priority; 3 = Planned; 4 = Telephone resolution; 5 = Police report only). An increase in the unit for this variable therefore indicates a lower priority allocated. The model suggests that, with all other explanatory variables held constant, for each unit increase in the response given in the first event, the mean severity is estimated to be 1.442 higher than if the event was graded with one grade lower (though higher scoring) priority. A consequence of including the response grade as a categorical variable is the assumption that the difference between each level of the variable is equal, which may not be the case. The arrest estimate suggests that, with all other explanatory variables held constant, dyads with at least one arrest have on average an estimated mean severity of 3.051 higher than dyads without an arrest. The crimed estimate indicates that, with all other explanatory variables held constant, dyads where the first event was recorded as a crime by the police, the mean severity score is estimated to be 2.966 higher than if the first event was not recorded as a crime.

Table 5.68 Final model of significant predictors on the mean severity score per dyad

Predictor	Estimate	Standard Error	p-value	Significance
Intercept	-1.287	1.294	0.32765	
Response grade (1-5) in the first recorded event	1.442	0.480	<0.01	**
At least one arrest	3.051	1.142	<0.05	*
Event crimed in the first recorded event	2.966	1.085	<0.05	*

5.3.3.2. Summary

The regression model examined whether any of the explanatory variables of police action and individual factors had a significant effect on the mean severity score of events experienced by dyads. Three variables of police actions were significant: response grade, arrest, and whether the event was crimed. The response variable suggested that dyads with a lower priority grading in the first event had a higher mean severity score than those with higher response grades in the first event. Dyads with at least one perpetrator arrest in the trajectory were estimated to have an increase in mean severity score by 3.051 compared to dyads with no arrest. Dyads where the first event was crimed were also estimated to have a higher mean severity score than dyads where the first event was not crimed. These results indicate that there is some association between these police actions and the average severity of events experienced by the dyads that come to force attention. The results do not provide information on why these particular police actions are associated with higher mean severity scores in dyads. The analysis also does not account for how many times the action occurred within a dyad trajectory. These are areas for further exploration to better understand the relationships between police actions and DVA severity that are beyond the scope of this analysis, though these findings have demonstrated that there are significant associations that warrant investigation.

5.4. Conclusion

The thesis is focused on improving the measurement of DVA in police data, and is primarily led by methodological research questions on the nature of the police data on DVA. To examine how police data could be improved, a new dataset was curated through the reconstruction of existing police data into a quantitative format that enabled the statistical analysis of DVA repetition and police action. The analysis intends to demonstrate the potential of police data to measure DVA repetition and police action if reconstructed into a theory-driven measurement framework. This chapter presented the results of the statistical analyses. The analyses were structured by two sets of research questions. The first set centred on the nature of DVA, referring to persistent debates in DVA theory. The second set focused on investigating any relationship between actions taken by the police and DVA repetition.

On the gender distribution of DVA, the analysis demonstrated that when frequency was counted as well as prevalence, the majority of DVA was against women. Descriptive analysis of derived variables and manual plots of dyad trajectories indicated that there was some escalation in frequency and/or severity for some dyads. However, when placed in a latent trajectory analysis, the results indicated that there was two identifiable trajectories of DVA when looking at frequency, and both decreased in frequency over time, whilst severity neither consistently increased nor decreased.

When investigating any relationship between police actions and DVA repetition, the analysis looked firstly at any association between police actions and the frequency trajectories, and then at both frequency and severity in separate regression analyses. Tests for significance indicated that arrest, referrals to probation; health; mental health; CSC; CFW; ASC; 'Other' and/or MARAC had some significant association with the frequency trajectory that a dyad belonged to, though this test did not indicate the size or direction of the relationship. Regression analyses for frequency found that when all available measures of police action were included in a model, only referral to MARAC had a significant effect on a dyad's frequency rate. Regression analyses for severity indicated that the priority response grade; at least one arrest of the perpetrator and the first recorded event being crimed were all significantly associated with the mean severity score experienced by a dyad.

The analysis demonstrates the ability to use police data to test patterns of repeat DVA and to investigate any relationships between police action and DVA repetition. The results are discussed in relation to the thesis research questions and with reference to the literature in the subsequent Discussion chapter.

6. Discussion

6.1. Introduction

The previous two chapters have presented two sets of results. The first, Results One, outlined the procedure for curating a new dataset through the reconstruction of multiple police data sources. The reconstruction intended to structure the data into a format that enabled the statistical analysis of DVA patterns and assessment of police action. The second, Results Two, presented the results of statistical analyses of the new dataset to demonstrate the potential of police data to measure DVA repetition and police action. The purpose of this Discussion chapter is to connect the findings to the questions of the thesis and the literature discussed in the Literature Review.

Though the core outputs of the thesis are methodological, the measurement focus is driven by the perceived substantive implications that improving the measurement of DVA repetition in police data would have for police practice and for theory. There were three main research questions:

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

Each question recognises the complex process of the police response to DVA, the stages and personnel involved, the existing mechanisms of data collection, sharing and access, and the force information systems in use. This chapter will outline the key challenges in police practice and DVA theory that underpin this thesis. The methods taken to address these challenges, the results and the implications for police practice and theory will be discussed, referring back to the existing literature in these areas. The chapter will conclude with the limitations of the thesis, setting up a future research agenda for policing and DVA theory, which is presented in the subsequent and final Conclusion chapter of the thesis.

6.2. Existing challenges in policing

As discussed in the Literature Review, over the last decade police forces in England and Wales have been challenged with maintaining an effect police service under stretched resources following a cut to their central government funding in 2010 (HM Treasury, 2010; HMIC, 2011). With stretched resources and growing demand, police forces need to effectively target resources to manage demand and reduce crime. DVA is a key contributor to police demand. HMIC (2014a) state that for police forces, DVA 'is a significant proportion of their violent, complex and resource intensive demand' (HMIC, 2014b: 12). DVA is a repeat crime, and thus targeting DVA repetition could be an effective use of police resources and have the potential to reduce the total amount of DVA. In their published approach to tackling DVA, Lancashire Constabulary estimated that 7% of calls for assistance and 10% of all recorded crime were DVA-related. The force were unable to provide data on the number of calls for assistance that were attributable to repeat victims (HMIC, 2014c).

Before the police can understand patterns of DVA and target resources, forces must have accurate information on repetition. Police forces collect information on incidents, victims, perpetrators, vulnerable persons and local areas, and all of this information is important for the police to understand their demand (HMIC, 2017). However, previous research and inspections of police forces have identified multiple issues that prevent the usability of police data for measuring DVA repetition, and demand more broadly. HMIC (2017) argue that poor and outdated information systems across police forces reduce the accessibility of data, and prevent information being quickly shared across police personnel. The lack of accessible data jeopardises public safety as responding practitioners are not receiving vital information when responding to calls for service (HMIC, 2017). For DVA specifically, HMICFRS (2017) found that some police forces struggle to identify repeat victims of DVA due to poor information systems. The inspection emphasised that accurate recording of DVA events, and their repetition, is vital to ensure the appropriate resources are allocated in a timely manner to ensure the victim as well as any children are safeguarded.

Lancashire Constabulary recognised that a considerable proportion of their demand was attributable to DVA, and much of this was repetition. As discussed throughout, to understand their demand and whether any police actions could reduce DVA repetition requires accurate and accessible information on victims, perpetrators, events and police action. Lancashire Constabulary was an early adopter of flagging, and had been flagging crimes and incidents with domestic flags prior to the Home Office requirement. Lancashire was therefore unique in having data on DVA crimes, victims and perpetrators over an extensive period, which should make the force an ideal site for measuring DVA repetition. The thesis sought to identify the data relating to DVA that is collected by Lancashire Constabulary, to identify whether the data can be used to measure DVA repetition and to consider how data and mechanisms of collecting and sharing information could be improved. A combination of observations and interactions with the force, data extraction, formatting and analysis identified multiple sources of police data relevant to the response to DVA and concluded that the data in their current form could not sufficiently capture DVA repetition. As the data could not capture repetition, it was also concluded that it would not be possible to assess whether any police actions had any impact on DVA repetition.

6.2.1. Identified issues in existing police data that determined the data were unsuitable for measuring DVA repetition

The research started with exploratory analysis of four datasets that were extracted directly from force systems with police analysts. The datasets were selected to collate information on the victim, perpetrator, event and any police action. The datasets were recorded crime, offenders, incidents and DASH. Each was extracted as a separate dataset due to information being recorded on different information systems. The datasets were extracted using standard fields in police systems. The data were largely quantitative and consisted of categorical and numerical information. Though mostly quantitative, there were some free-text fields in the crime data written by responding officers.

The aim was to merge the datasets to produce one quantitative dataset for statistical analysis that combined as much information as available on victims, perpetrators, events and police action. Initial formatting and exploratory analysis determined that the data could not measure DVA repetition. There were four key reasons that the data were deemed unsuitable for measuring DVA repetition and police action: different units of measurement, inconsistent recording of personal details, inappropriate application of DVA flags, and the loss of information in free-text narratives.

To measure DVA repetition requires at least three units of measurement: victim, perpetrator, event (Walby et al, 2017). An additional unit of measurement found in analyses of DVA is the dyad (Bland and Ariel, 2015). As victim and perpetrator information was not available in each dataset, repeat individuals could not be matched across datasets. Victim/perpetrator information was only available for the crime data, thus individuals could not be identified in the incident data. Around half of DVA reports to the police do not result in a crime report (ONS, 2019b), thus using crime data alone to measure repetition would omit around half of DVA that is reported to police.

Further issues were found when trying to identify repetition within the same datasets. To identify repeat individuals, personal details such as name, address and DOB are often used (Brimicombe, 2016). The accuracy of any estimate of repetition is improved when all personal details are recorded, as it increases the likelihood of the same persons being identified (Brimicombe, 2016). As found in previous analyses of police data (Brimicombe, 2016), the personal detail variables within the datasets provided by the force had lots of missing information with personal details inconsistently recorded between events. In the crime data, the force did apply a unique ID to each victim and perpetrator that combined the individual's name and DOB, though as with other personal details, this was recorded inconsistently. Furthermore, when personal details were recorded, they were sometimes recorded in different formats, using different spellings and punctuation. This prevented the matching of repeat individuals, and required extensive and time-consuming manual editing to ensure matching records were in the same format and could be recognised by statistical software. This is a persistent problem in police data that has been found in previous analyses of DVA (Farrell and Pease, 1993; Bland and Ariel, 2015; Brimicombe, 2016). Another barrier to matching repeat individuals using personal details is that these details may change over time, this may be particularly relevant for DVA. For instance, within the datasets, the same victims and perpetrators appeared under multiple home addresses. When leaving DVA, victims are often forced to relocate multiple times to evade the perpetrator, and may move between multiple addresses, including staying with family and friends and in temporary refuge accommodation (Bowstead, 2015; 2017). The same victims may have appeared under different surnames throughout the dataset, for instance due to a change in marital status, with separation being a common risk factor for DVA (Barnish, 2004).

The third issue was the multiple methods of marking DVA in police data, and the inaccurate use of DVA flags. All crimes that fit the Home Office definition of DVA should be given a DVA flag, and all crimes that fit the definition of repeat DVA should be given an additional 'repeat DA' flag. Some of the crimes in the recorded crime data did not fit the definition of DVA, suggesting misapplication of the DVA flag. For instance, an assault against a PC when responding to a DVA-related event does not fit the DVA definition, as the PC is not the victim of DVA, though several assaults against constables appeared in the police extracted DVA crime data. Events such as this are more likely to be singular than repeat events, therefore having several misclassified single events in the DVA data could affect overall measure of DVA repetition. In addition to the misuse of DVA flags, the existence of multiple flags/codes to identify DVA across police systems provided further complications. In addition to the DVA and repeat DA flags for crimes, the force also had two domestic flags for incidents/non-crimed events, and two domestic incident codes. DVA events may be recorded under different combinations of flags and codes, and therefore selecting one flag/code to extract a sample of DVA events will produce a different sample of events than if another flag/code was used. Furthermore, the DVA response required additional information collecting such as DA referrals and DASH, which each provide their own DVA sample. The multiple methods of recording and identifying DVA produced multiple overlapping though not matching samples of DVA events, and each may produce a different measure of repetition.

The final issue identified in the existing police datasets is that additional information that could contribute towards understandings of DVA was lost in free-text narratives. As found by Bland and Ariel (2015), the free-text presented a barrier to analysis, as the information requires extensive reading and coding to be used, thus for Bland and Ariel free-text police data was largely excluded from their analysis. In the recorded crime data, some of the free-text crime fields were read to consider the type of information recorded in police summaries. In some cases, the free-text indicated that there were other DVA offences that took place but were not captured by the standard fields, therefore suggesting that the available quantitative data underestimated the extent of DVA repetition and some offences may not have been crimed. In most cases, the free-text provided additional detail about the event, victim and perpetrator that could contribute towards understanding patterns of repetition and police action. Such factors included the history of violence between victim and perpetrator, whether multiple offences took place in one event, any personal and situational factors relating to the victim and perpetrator, and contextual information on the action the police took, or did not take.

The immediate impact of not having accurate and accessible data on DVA repetition is that vital information on victims, perpetrators and their history of violence may not reach responding practitioners. This lack of or delayed access to information inhibits their ability to tailor response and to target resources appropriately and in a timely manner, thus putting the safety of the victim and wider public at risk (HMICFRS, 2017; HMIC, 2017). The longer-term impact of poor data collection is the prevention of robust statistical analysis of DVA repetition and assessment of police actions on DVA repetition. This research could be conducted by the police in-house, academics or other agencies that could inform the police on patterns of DVA repetition and police action and aid decision-making and resource allocation to improve the effectiveness of actions and interventions on the reduction of DVA.

6.2.2. Improving police data to measure demand and evaluate the effectiveness of police action

As discussed, to measure DVA repetition requires data on the event, victim and perpetrator, and repetition must account for both frequency and severity (Walby et al, 2017). To evaluate the effect of police action on DVA repetition requires data on the actions taken by police. Additional factors that may affect the effect of police action on DVA such as the sex of the victim and perpetrator (Stark, 2007; Johnson, 2008; Walby and Towers, 2018), socioeconomics (Walby and Allen, 2004; Towers, 2015; Walby and Towers, 2018), physical and mental health (Walby and Myhill, 2001) and previous violence (Pease and Laycock, 1999) should be controlled for.

Observations of the force provided enough information to map out the police response, to visibly demonstrate the complexity, the various stages involved and the points of data collection and available data sources. From this mapping, four data sources were selected that contained information on the victim and perpetrator, including the additional factors listed above, circumstances of the event and actions taken by the police and other agencies. These four data sources were DA referrals, DASH, crime reports and incident reports. As each data source was stored within a different information system in various formats, the data were reconstructed into one quantitative dataset to enable statistical analysis. From the existing literature and knowledge of police systems and data gathered through interactions with the police, a measurement framework was derived to guide the restructure of the data. The measurement framework lists the units of measurement to be included in the dataset, namely the victim, perpetrator, dyad and the event, and the variables that should be included. The categories are police action (explanatory), repetition (dependent), victim (control), perpetrator (control), dyad (control) and event (control). The framework is presented in Table 4.1 of the Results One chapter.

The DA referral should be submitted for all DVA events regardless of whether crimed, and the referral must name a lead referral, usually the victim, as the target for safeguarding. The events in referrals should therefore reflect the DVA definition and be less subject to the misapplication of DVA flags than the recorded crime data. The referrals were treated as the base sample in the curated dataset, and information from the three other sources were added. Most information in the referral was free-text, thus the dataset curation required extensive manual reading/coding of the information into a quantitative form. Due to the time-consuming task of manually recoding information from four data sources, the curated dataset has a relatively small sample of 325 events relating to 68 victims and 94 perpetrators. Statistical analyses of the dataset served to demonstrate the potential of police data to measure DVA repetition and police actions when structured in a measurement framework designed to analyse patterns of DVA and assess police action. Due to the small sample size, the results of the analyses may not be interpretable beyond the cases within the sample. For policing, the analyses examined the estimated repetition, and investigated whether there was any association between actions taken by the police and DVA repetition.

Firstly, the curated dataset provided a more accurate measure of repetition than the existing police datasets. In the curated dataset, 51% of victims had two or more recorded DVA over a three-year period. This is compared to the crime dataset provided by the force, where 21% of victims had two or more recorded crimes in the same three-year period. Part of this difference was explained by the inclusion of non-crimed events in the curated dataset. Crime data do not include non-crimed events, therefore they cannot contribute towards the estimate of repetition. The difference between the repetition estimate in the curated dataset and the crime data may also be partially explained by the type of events that were included in the curated dataset. The curated dataset was based on a sample of DA referrals. DA referrals are only submitted for DVA events, and must include the victim and perpetrator and state the relationship between the two within the referral. Singular events that were misclassified as DVA in the crime data, such as an assault on a constable, did not appear in the referral data and thus did not skew the repetition estimate.

Secondly, the curated dataset was able to examine the actions taken by the police in response to DVA and investigate any relationships between police actions and DVA repetition for the dyads captured in the sample. This was due to the additional information extracted into the dataset on police action, including information sharing and multi-agency working, which was not available in the existing police datasets. This information was already collected by the police, and the curated dataset enabled the data to be considered in analysis. The analysis then assessed for any relationships between the frequency and severity of DVA for dyads in the dataset, and actions taken by the police.

6.2.2.1. Police action in response to DVA

Analyses of police action refers only to the police actions that were available in the dataset, and do not include all actions that could possibly be taken by police forces in response to DVA. Analysis looked at response grades allocated by police call-handlers, risk assessment and classification, arrest and referral to other agencies. The most common response grade allocated to DVA events was emergency response (44%), followed by priority response (30%), planned response (21%) and telephone resolution (5%). None of the events in the dataset received the lowest response grade of a police report only. When looking at the total demand received by one police force, Boulton et al (2017) found that of all calls for police service (non-DVA and DVA), the most common response grade given was the planned response (29%), and the least common was the emergency response (7%). The findings suggest the DVA events in the dataset were given greater priority by police call-handlers than the average reported event.

For two-fifths (40%) of events in the dataset, no DASH was completed due to victim refusal or non-completion by officers. This may be partially explained by findings in the literature that the use of risk assessment tools by responding police officers is inconsistent, and often risk assessments are left incomplete or partially complete (Robinson et al, 2016). Where a risk assessment was not completed, a risk classification was still assigned. The most common risk classification given was standard-risk (52%), which elicits the lowest level of police action, 28% of events were graded as medium and less than a fifth (19%) as high-risk. The high-risk classification yields the most active police response (Robinson et al, 2016). Most events thus received the minimal police response of safeguarding and investigation. Robinson et al also found that when making a risk classification, officers often prioritised physical violence and physical injury when allocating high-risk classifications, thus not recognising the risk posed by non-physical forms of abuse. Beyond police use of the risk assessment, the DASH tool itself has been criticised as ineffective for predicting repeat victimisation (Almond et al, 2017; Turner et al, 2017).

Of all events, just under a third (33%) led to a perpetrator arrest. Within crimed events, this was less than half (46%). This differs to the HMIC (2014c) report in which Lancashire Constabulary report that 90% of their DVA recorded crimes result in arrest of the perpetrator. The CoP (2018b) states that in cases of DVA, the police are encouraged to take 'positive action', which usually means arrest of the perpetrator, though the decision down to the judgement of the responding officer(s). The findings suggest that in most cases the police decision has been to not arrest. The percentage that led to arrest is lower than the average arrest rate of 45% for DVA events in England and Wales (HMICFRS, 2019). HMICFRS expressed concern over the low and declining arrest rates for DVA cases across England and Wales, and have called for forces to improve their understanding of reasons for the declining levels of arrest. The free-text information did not provide reason for non-arrests. From the literature, some reasons for low arrest rate may be that the officer(s) did not feel that arrest was appropriate due to circumstances of the event or a lack of cooperation from the victim (Hoyle and Sanders, 2000; Birdsall et al, 2017; 2020); a lack of available resources to pursue the case (UNISON, 2018); or another form of positive action was taken, such as DVPN/DVPO (Birdsall et al, 2017).

Of all DVA events in the dataset, 62% were referred to at least one other agency (e.g. probation, IDVA, health, CSC). In crimed events, this was almost three quarters (73%). Based on the findings of the literature which has shown specialist support for DVA victims can improve victim wellbeing and empower victims to leave perpetrators (Hoyle and Sanders, 2000; Robinson, 2009; Howarth et al, 2009), the finding that most events are shared with at least one other agency should be a positive outcome for victims. There was no further information on action taken by agencies, thus it is unknown whether any safeguarding measures were put in in place for the victim followingreferral. Furthermore, Hoyle and Sanders (2000) suggested that both arrest and safeguarding are needed to effectively prevent repeat DVA, as the arrest of the perpetrator provides the victim with time to engage with safeguarding plans whilst receiving support, though most cases did not result in an arrest or criminal investigation. Hoyle and Sanders also stated that specialist support needs to be provided in the immediate aftermath, though Shorrock et al (2019; 2020) have identified that the ability of safeguarding networks to provide immediate support has been prevented by demand that exceeds capacity.

When an event was crimed, the most common police recorded outcome was NFA (62%). Within the NFA crimes, the most common crime status to explain the NFA was 'Evidential difficulties victim based - named suspect identified' (58%). During the observations of the police response, it was learned that the police often felt challenged in their capacity to pursue investigation in DVA cases due to victim withdrawal and lack of cooperation with the police. The issue of victim withdrawal for police investigation has been consistently raised in the literature (Hoyle, 1998; Sleath and Smith, 2017; Birdsall et al, 2017). Hoyle and Sanders (2000) found that victims often withdrew their cooperation with the police response following arrest as they felt the arrest had successfully achieved what the victim wanted, or due to fear of further and more severe violence from the perpetrator. One response from the CJS to handle victim withdrawals has been to pursue victimless prosecutions, though this fails to recognise the controlling context in which DVA occurs and prioritises prosecution over successfully stopping the violence (Hoyle and Sanders, 2000). Victim engagement with the CJS process can be improved when the victim is provided with specialist support which can lead to more arrests and prosecutions (Hoyle and Sanders, 2000; Howarth et al, 2009; Sleath and Smith, 2017), though the police response to DVA should also recognise that prosecution may not be in the best interests of the victim and thus victim needs should be considered in decision making (Sleath and Smith, 2017; Birdsall et al, 2017). Birdsall et al (2017) called for a victim empowerment approach to the police response to DVA, which is not centred on victim choice nor pro-prosecution, but accounts for the unique factors that affect each DVA event and victim to understand their engagement with the police and tailor an appropriate response. To take a victim empowerment approach and tailor responses to the circumstances of the case requires that information be collected on the event, victim and perpetrator.

6.2.2.2. Relationship between police action and repetition

This analysis compared the effects of multiple components of the police response with the frequency and severity of DVA. The analysis firstly focused on arrest and referral to agencies, and tested their association with the frequency of DVA. In this analysis, frequency was measured using two frequency trajectories identified in the latent trajectory analysis. Both trajectories showed a pattern of decreasing over time, though the largest trajectory showed a starting point of low frequency, and the second smaller trajectory showed a high frequency starting point. The analysis did not identify any distinguishable trajectories of severity. Significant associations were found between arrest; referral to probation; health; mental health; Children's Social Care; Child and Family Wellbeing; Adult Social Care; MARAC; and referral to other unlisted agencies. The analysis does not provide an information on the direction or the size of the relationship, though the difference in percentages of dyads in each group receiving each response indicate that dyads in the higher frequency group were more likely to have received an arrest or referral. More dyads in this group had a greater number of events, which may have provided more opportunity for a response to occur. The analysis does not indicate at which event the response occurred.

The main analyses on the relationship between police action and repeat DVA were two regression models. The first was a Poisson log-linear regression model, treating dyads frequency rate per year as the dependent variable, and measures of police action, victim/perpetrator sex and relationship as explanatory. Police action variables included response grade, risk level, arrest, charge, crime status and referral (disaggregated by agency). In the frequency regression, the model which best fitted the data suggested having at least one referral to MARAC was significantly associated with a higher frequency rate. The analysis did not distinguish the number of times a dyad was referred to MARAC, nor at what point in the dyad's trajectory that the referral occurred. Therefore, rather than indicating that a referral to MARAC precedes an increase in frequency rate, it is likely that dyads with a higher frequency rate are more likely to have had a referral to MARAC. As discussed in the Literature Review, an evaluation into the effectiveness found that around 60% of victims that received a MARAC had not been re-victimised in the six months following their MARAC (Robinson, 2004). Robinson et al (2004) also found that more than three quarters (77%) of victims had previously reported DVA to the police prior to their MARAC, and more than half (52%) had two or more. This literature would support the interpretation of the present study's analysis findings that a high frequency of DVA events reported to the police would precede a MARAC referral.

The second regression model was a linear regression model, treating the average event severity score experienced by dyads as the dependent variable. The severity regression found that of all explanatory variables, the response grading given in the first event; at least one arrest of the perpetrator; and whether the event was crimed in the first event were all significantly associated with higher average severity scores. Interestingly for response grading, the analysis indicated that dyads who received a lower priority response grade in their first recorded event, for instance a priority (police attendance within one hour) rather than an emergency response grade (police attendance within 15 minutes), were likely to have a higher average severity score. HMICFRS' (2019) inspection expressed concern that the police were sometimes too slow in attending DVA events. They state that delays in attendance can be damaging for the investigation and put the victim at risk of serious harm, and report finding delays in over a quarter of police forces in England and Wales. In some forces, HMICRS found that delays in response were due to an inability of the police to respond immediately in times of high demand due to a lack of resources. Delays in response may also prevent positive action as the opportunity to arrest may pass before the police attend. The analysis found at least one perpetrator arrest to be associated with a higher average severity score. The analysis did not account for how many arrests the dyad experienced or the point in the trajectory where arrest was made. The significant relationship may not reflect higher severity of DVA following arrest, but instead indicate that dyads with higher severity scoring events are more likely to experience arrest. The severity scores are based on offence types, with violence resulting in injury and sexual offences scoring higher (Heeks et al, 2018). Myhill (2019) found that police officers' often prioritised physical assault and injury with seriousness, reason for arrest and sufficient evidence that an offence has occurred. The results could therefore indicate that events scoring higher in severity scores, particularly those involving physical assault and injury, were more likely to experience an arrest. Similarly, the analysis found that dyads where the first recorded event was crimed by the force were more likely to have a higher average severity score than those whose first event was not crimed. Myhill found that events that involved physical assault and injury were more likely to be deemed as indicative of a crime occurring by officers than offences that did not.

Overall, the primary purpose of the analyses of police action was to demonstrate the potential of police data to assess relationships between different forms of police action, including information sharing/multi-agency working, when data are structured following the thesis' measurement framework. The framework increases the estimate of repetition, and allows for more types of police action to be considered. The results indicate that there may be some association between specific measures of police action and the frequency/severity of DVA. However, there are several limitations to the analysis, presented later in this chapter. Key outputs and implications of improved measurement on police practice and policy

There are several outputs from the thesis that have implications for police policy and practice. These outputs are primarily methodological though have substantive implications for policy and practice. The first output is a map of the police force's response to DVA, shown in Figure 3.9. The map is a simplified overview of the police response to DVA, highlighting just some of the initial actions taken by the police, and focusing on the collection and sharing of data. This response map provides the force with a clear visual that demonstrates just some of the complexity involved in their response, and the various stages and personnel that information passes through. The map indicates how information collected in specific stages of the response is used later in the response when making decisions on safeguarding and interventions, thus emphasising the importance of accurate and detailed information recording. For instance, the information collected by the call handler in the incident report will be filtered to frontline officers, which may influence actions they take if and when they attend the event. Information is then added to the incident report, which will later be used to submit a referral for safeguarding of the victim to MASH, alongside additional information collected in DASH. Information available in the referral and DASH will be reviewed by MASH to determine what safeguarding measures to put in place, including a referral to MARAC and other agencies. The information collected in the incident report and any other information collected in response such as victim/witness statements and DASH may determine whether responding officers record the event as a crime. The information recorded in the crime report, along with footage collected by BWV, may then be considered by CID to build a case against the perpetrator which may then be submitted to CPS.

This is a summarised account of the journey information makes throughout the response, and the implications that poor recording of information at various stages can have on the actions that are available and taken. For police practice, this map should reemphasise and encourage accurate and detailed information recording and sharing at every stage of the response. The map also demonstrates points where the recording of information may be duplicated. For instance, responding officers summarise the event and the action taken in the incident report, may provide a smaller summary in a crime report, and then write an extensive account in a referral to MASH. In practice, response officers could save time and reduce any inconsistency between accounts if these data sources were combined in one report, to which MASH have access. This is an approach embedded into the new information systems that were implemented in Lancashire Constabulary in November 2018. Rather than a separate incident report, crime report and referral, the new system has one investigation file. The new investigation format is opened for any event, with additional standard fields to be completed if the event results in a recorded crime, and a tick box that identifies whether the event needs to be referred to MASH. If this box is ticked, MASH receive a notification for referral and will review the case. DASH is also attached to the investigation. At the time of study, the force were still implementing and adjusting to the new system. Following this study, it is of interest to conduct a follow-up analysis of data extracted from the new system to determine whether the accessibility and usability of information has improved.

The second key output is a measurement framework for collecting data on DVA, including a set of criteria for future data collection. The measurement framework is presented in Table 4.1, and the criteria for data collection in Table 4.3. The measurement framework was derived from existing DVA theories, the police concern with demand and police action, and knowledge of police data and information systems gathered from interactions with the police. The framework lists the measures that should be included in analysis to understand DVA repetition and to assess the impact of police action. For practice, the availability of this information to responding practitioners would increase if collected as standard fields. Information that could help police and other agency decision making on actions, interventions and risk assessment, such as whether the victim or perpetrator have a mental health problem, the number of previous call outs and what action was taken in the previous call outs would be more accessible to responding practitioners if recorded as standard fields and attached to victims and perpetrators. This information is already collected by the police though is embedded within free-text narratives, which take longer to record. This is not to suggest that free-text should be removed from police information systems, as the text is important for providing context to the complexities and circumstances of DVA, but that the amount of free-text required could be reduced with standard fields. The study was limited by time and the information available in the selected data sources, though the police are recommended to expand the framework to include additional forms of police and wider CJS action and interventions, such as prosecution and offender programmes.

As discussed, exploratory analysis of the original police datasets identified a number of issues that prevented the ability of police data to measure DVA repetition and police action. A new dataset was curated and analysed to demonstrate the potential of police data when reconstructed using the above framework. From all stages of the research, a set of criteria for future police data collection was derived. The criteria include the use of the measurement framework, the inclusion of the event, victim, perpetrator as units of measurement and the merging of data sources into one information system.

The criteria also state that victims and perpetrators (both suspects and offenders) should be assigned a unique ID that is a combination of numbers rather than a merging of personal details, as was found in the original force crime data. The use of a unique nominal assigned to each individual would override some of the issues found in the use of personal details for matching repeat individuals in the existing datasets, particularly partially missing data. The nominal would need to be consistently recorded for every individual in every event. Part of the force's new information system includes the allocation of a nominal to victims and offenders, which should aid the identification of repeat individuals and increase the accessibility of information on a victim and/or offender's history for practitioners. At the time of study, the nominal system was in the process of being implemented and the force were undergoing the huge task of backdating records to attach nominal identifiers to individuals across systems. Though too soon to consider whether the new system had improved the identification of repeat individuals, it was recognised that the inconsistent recording of personal details could still prevent the nominal being attached to the same individual, thus care and consistency in data recording is still necessary.

The criteria also state that one DVA flag should be used to identify DVA in police data, and the flag should be attached to events that fit the DVA definition. To resolve the existing problem of too many flags and misapplication would require greater police understanding of DVA and when to apply a DVA flag to an event, and to only have one domestic flag to identify DVA within events, regardless of whether the event was crimed. There would also need to be greater consistency in officer completion of information recording tasks in DVA, to ensure any additional data sources such as the DA referral and DASH are available for every event. The findings suggest that adding new flags to police data, as has been the Home Office (2020a) response with the new repeat DA flag, does not improve the estimate of repeat DVA in police data but instead may contribute to further underestimations of repetition. The addition of a new flag does not address the underlying issues in police data recording, and instead further complicates already complex systems of data recording.

The framework and criteria for data collection have implications for police policy on data collection and sharing for DVA, and perhaps more broadly. The police collect lots of data, but when these data are not readily accessible to practitioners, the information is redundant and puts public safety at risk (HMIC, 2017). Combining multiple sources of police data and revising the standard fields available in police information systems could increase the accessibility of police data to responding practitioners and aid the police and other agencies to tailor their response and resources. This thesis thus recommends that the findings lead to the construction of policy on DVA data collection, and wider crime and vulnerability, that embeds the measurement framework and criteria for future data collection into practice. The policy may require that the measures laid out in the framework are always collected when responding to DVA, and that information systems be reviewed and possibly revised to embed the principles laid out in the criteria for future police data collection.

A third output is the findings of the statistical analysis. The core aim of the statistical analysis of police action and DVA repetition was to test and demonstrate the potential of police data to measure DVA repetition and to assess the impact of police actions. The analysis was conducted on a small sample size, thus the results may not be generalizable beyond the specific dyads in the dataset. However, the analysis did suggest some associations between certain police actions and DVA that may prompt further exploration by Lancashire Constabulary or prompt an area for further research. Some findings of interest include that over a third (36%) of DASH were recorded as having being refused by the victim, and a further 4% were indicative of non-completion by the police based on the information available. DASH should be completed for all DVA events, and the risk classification allocated from DASH contributes to decisions on actions taken by the police and agencies in response to DVA (Richards, 2009). It may be of interest to examine whether this large proportion of refusals would be found in a much larger and more recent sample of DVA cases, and to look into the cases that refuse and determine whether there are common circumstances or individual factors that are associated with refusal. Another finding of interest was that less than half (46%) of crimed events led to the arrest of the perpetrator. In the crimes that resulted in NFA, the most common reason was victim based evidential difficulties (58%). It may be of interest to investigate whether there is a relationship between victim engagement and the likelihood of perpetrator arrest, following on from the findings of Myhill (2019) that officers were less likely to arrest when they felt the victim was unlikely to support the case. It is important to note that the percentages in the dataset are based on cases recorded over 15 years, and there may be considerable variation in the actions often taken in the most recent years than earlier years. Nevertheless, these findings prompt further investigation. On the association between specific police actions and DVA repetition, namely referral to MARAC; the priority response grade; arrest; and whether the first recorded event was crimed, which were all significantly associated with the frequency or severity or DVA in the regression analyses, these relationships should be re-examined in a much larger dataset.

A fourth output for police policy and practice, specifically the work of the EBP Hub, is the methodology for reconstructing existing sources of police data to facilitate analysis on DVA that comes to police attention, and the efficacy of police actions. To the best of the researcher's knowledge, police data have not previously been used in this way to measure DVA and evaluate policing, this is a new methodology. Reconstructing police data could enable further research to answer specific questions on the relationship between actions taken by the police and partner agencies and the frequency and severity of DVA that is repeatedly reported to the police. Answering these questions could guide the targeting of funding and resources to interventions found to prevent the escalation of DVA and reduce harm to victims.

This leads to the final implication for policing, the perceived long-term impact of revised mechanisms of data collection, sharing and analysis within police forces and the wider CJS, which is increased effectiveness in the targeting of police resources to reduce DVA repetition. With an improved measurement framework, the police would be better able to accurately identify and measure DVA repetition and to analyse the impact of specific actions on DVA repetition. Such analysis would increase the evidence base for 'what works' in tackling the DVA that comes to police attention.

6.3. Existing challenges in the theory of domestic violence and abuse

As discussed in the literature, there are competing theories of DVA, and these theories have influenced police practice. The aim of this analysis was to test the potential of police data to measure the characteristics of the DVA events, victims and perpetrators in the curated dataset. Due to the small sample size of the dataset, the findings are interpreted only as characteristics of the study sample and not as representative of the wider DVA population. The analysis looked at the characteristics of victims, perpetrators and events that came to the attention of the force within the sample. The analyses then focused on the sex distribution of DVA within the dataset, and then on patterns of repetition in DVA, looking at frequency and severity.

6.3.1. Testing theories of domestic violence and abuse using police data

Central to ongoing debates are the extent to which DVA is gendered, escalates over time and whether differences in identified patterns of DVA represent different types of DVA. The theories were tested through statistical analyses of the curated dataset to test the ability of reconstructed police data to measure DVA repetition. The analysis first considered the sex distribution of DVA. Debates have long contested whether DVA is predominantly men against women (Dobash and Dobash, 1979; 2004) or whether DVA is gender symmetrical (Straus, 1979). Walby et al (2017) argue that DVA is gendered and is largely a crime committed by men against women, and that to show the gendering of DVA requires robust measurement and recognition of frequency and severity as well as prevalence. The analysis therefore examined the prevalence of female and male victims and perpetrators in the dataset and examined the average number and severity of events experienced and perpetrated by females and males.

The analysis then focused on patterns of escalation in the data. The core stages of this analysis were two latent trajectory analyses that tested separate trajectories of escalation for frequency and severity for dyads that had two or more events in the data. Three hypotheses were tested to examine whether the selected theories taken from the Literature Review could be reflected in the curated dataset. The first theory was one trajectory of DVA that escalates in frequency and/or severity over time, taken from Walby and Towers' (2018) concept of domestic violent crime, which states any observed differences in patterns of DVA represent different points in an escalation trajectory rather than different forms of DVA. The second theory was two trajectories, with one showing a pattern over time of escalating frequency and/or severity, and the second showing a relatively stable and low frequency and severity trajectory that does not escalate over time. This is derived from Johnson's (2008) typology of DVA that suggests there are two main forms, intimate terrorism (frequent, controlling, escalatory, gender asymmetrical) and situational couple violence (infrequent, low severity, stable, gender symmetrical). The third theory is taken from criminal careers research, specifically Nagin and Land's (1993) three trajectories of offending. Nagin and Land found three offending trajectories: adolescent-limited (offending peaks at adolescence and then desists over time), low-rate chronic (low frequency lifetime offending) and high-rate chronic (high frequency lifetime offending). These trajectories have been adapted to hypothesise a deescalating trajectory, a stable trajectory, and an escalating trajectory. Table 5.34 shows the three hypotheses.

The final phase was a descriptive analysis of dyads with higher and lower frequency/severity, to consider whether the dataset sample supported existing theories that the most frequent and/or severe DVA is committed by men against women (Dobash and Dobash, 2004; Johnson, 2008), and particularly against women with lower socioeconomic status (Bland and Ariel, 2015; Walby and Towers, 2018). Descriptive analysis examined the proportion of dyads in low and high frequency trajectories that had female victims, male perpetrators and high unemployment.

6.3.1.1. Sex distribution of domestic violence and abuse

The force procedure for recording sex and gender was unknown and has likely changed over time due to the dataset covering a period of 15 years (2003 – 2018), therefore the recording of females and males in the data is assumed to be police identified sex, rather than gender. There was a fairly event proportion of female (53%) and male victims (47%), though males were the majority (78%) of perpetrators. Frequency was measured as the number of events experienced per victim. Overall, female victims experienced more than three times as many (247) events than male victims did (78). Multiple measures of severity were examined in the analyses. The simplest measure of severity is whether the event involved physical violence, and whether the violence led to injury. A greater percentage of events experienced by males (31%) involved physical violence with injury than of the events experience by females (17%). However, as females experienced a much higher number of events than males, the majority of events of physical violence with injury were against female victims and by male perpetrators. The analysis then graded event types with a severity score. The analysis found little difference in the average event severity experienced and perpetrated by females and males, though females experienced and males perpetrated the highest scoring events in this dataset, specifically rape. The findings show that when the frequency and severity are measured as well as prevalence, the distribution of sex can be seen and the majority of DVA is perpetrated by males towards females. The findings support the arguments that the frequency and severity of DVA need to be recognised and measured as well as prevalence when making conclusions on the experience of DVA by sex (Dobash and Dobash, 2004; Walby et al, 2016).

6.3.1.2. Escalation of domestic violence and abuse

This section of the analysis examined patterns of escalation in the dataset. The findings demonstrate the types of analysis that could be done if police data were reconstructed following the measurement framework. The findings are applied only to the dataset and are a product of the sample and analysis technique.

The latent trajectory analysis found that a model of two trajectories was the best fit to the frequency data. The two trajectories both showed declining frequency over time. The largest trajectory, that is the trajectory to which most dyads were allocated, showed a lower frequency decline over time. The second smaller trajectory showed a higher frequency decline over time. Each of the three hypotheses were therefore rejected, as none of the selected trajectory theories could explain the identified patterns of frequency in the curated dataset. Though there were two trajectories, both declined in frequency over time and therefore were not comparable to Johnson's escalating intimate terrorism and stable situational couple violence. The findings also do not correspond to previous research on the frequency of DVA patterns that come to police attention. Bland and Ariel (2015) found a significant relationship in the number of days between calls to police over time, indicating an increasing rate of frequency as the number of sequential events increased, treating the dyad as the unit of measurement. Brimicombe (2016) found an increase in the frequency of DVA calls to police in the lead up to a domestic homicide, treating the victim as the unit of measurement. Barnham et al (2017) found that the time between DVA events got progressively shorter as the number of events increased, indicating a rise in frequency over time, treating the offender as the unit of measurement.

For severity, the analysis indicated that the best fitting model was one trajectory classification, as the model worsened when additional classes were added. This means that no more than one trajectory pattern was identified in the data. This may indicate that the sample size of the data was too small to detect a pattern. Alternatively, the results could suggest that there is little variation in the patterns of severity that come to police attention. The severity trajectory fluctuated over time. The three hypotheses were again rejected, as the trajectory theories could not explain the severity patterns in the data. Though one trajectory, the pattern shows both escalation and de-escalation over time, therefore does not correspond to Walby and Towers' one trajectory of escalation. The trajectory shows persistent fluctuation, with no clear overall increase or decrease in severity over time. This somewhat differs to the findings of previous research on patterns of DVA severity over time in police data. Bland and Ariel (2015), Brimicombe (2016) and Barnham et al (2017) all stated that there was no evidence in their data of increasing severity.

Focusing less on the shape of the two frequency trajectories, the two groups were examined as a low frequency group of dyads and a high frequency group of dyads. The sex of the victim and perpetrator, employment status and relationship type as well as the number of events and maximum severity of events experienced by dyads were examined, to consider whether the dyads in the dataset supported theories that the most frequent and severe DVA is against women with lower socioeconomic status by men. Across all dyads in this stage of analysis, the majority of perpetrators were male (83%), victims female (60%) and dyads intimate partners (90%), and the employment rate was low (27% for victims and 33% for perpetrators). However, the percentages were greater when looking at high frequency dyads, with 83% male perpetrators, 83% female victims, all dyads intimate partner, and a lower victim employment rate of 17% (33% for perpetrators). All dyads that experienced the highest maximum severity scores were in the high frequency group. These proportions suggest the dyads of the curated dataset correspond with previous research that suggests the most frequent and severe DVA is by men against women, particularly against women with lower socioeconomic status (Johnson, 2008; Bland and Ariel, 2015; Walby and Towers, 2018).

There are several caveats to these findings, discussed in the limitations section to this chapter.

6.3.2. Outputs and implications of improved police measurement for domestic violence and abuse theory

The key outputs for theory are methodological: the measurement framework, criteria for future police data collection, and methodology for restructuring police data into this framework. The statistical analysis demonstrated that when police data are restructured following a measurement framework driven by theory, police data could be used to test DVA theories. Testing and challenging theories has implications for the response of the police and wider CJS, and therefore implications for victims and perpetrators of DVA.

The measurement framework is theory-driven and expands on existing frameworks for measuring DVA repetition (see Walby et al, 2017). The framework adds individual and social factors identified in the literature as associated with patterns of DVA, including socioeconomic factors, mental health and alcohol/substance misuse. As the thesis has focused on the measurement of DVA by police and the implications for police response, the framework adds police actions to enable the evaluation of whether any of the included police actions have an impact on patterns of DVA. The framework is iterative. As theories develop on the nature of DVA, on the causes and means for prevention, the factors included in the framework may update. As the police and CJS response continues to develop, additional actions and interventions may be added.

The methodology for restructuring police data to measure DVA repetition and police action may be used in future research by academics and other agencies, to maximise the use of police data to answer research questions on DVA. The methodology may be applied to other areas of crime and vulnerability within policing, or adapted to other forms of administrative data, including health and social care data. The methodology may be expanded to produce much larger datasets, using more researchers to read/code information, or sophisticated statistical techniques such as natural language processing to extract large quantities of data from free-text. The methodology of the thesis has implications for future research to develop theories using data that have previously been largely inaccessible.

The final implication for theory are the statistical analysis results. Though the main aim of the analysis was to consider the ability of police data to measure DVA patterns, the analysis results have prompted areas for further investigation in DVA theory. On the sex distribution, the analysis found that though the difference between the prevalence of females/males in the victim population appeared small, when frequency was measured it became visible that most DVA events were by males against females. This corresponds to t the literature that DVA is largely a problem of male violence against females (Dobash and Dobash, 1979; 2004) and that gender disparity is made visible when frequency as well as prevalence is taken into account (Bland and Ariel, 2015; Walby et al, 2017). On escalation, the analysis did not find evidence of escalating frequency, in comparison to previous studies on repeat DVA in police data (Bland and Ariel, 2015; Brimicombe, 2016; Barnham et al, 2017). This may be due to the small sample of cases in the analysis and requires further investigation. The analysis of severity indicated no distinct trajectory patterns, though did show fluctuation in severity over time. This requires further investigation to understand how severity may change over time, for instance with the inclusion of individual and social factors and agency interventions in the analysis. The analysis did find that within dyads with higher frequency, the majority of DVA was by males against females with lower socioeconomic status, supporting existing theories of DVA frequency (Walby and Towers, 2018) and previous research in the frequency of DVA that comes to police attention (Bland and Ariel, 2015).

6.4. Limitations and future research

Through the curation and statistical analysis of reconstructed police data, the thesis demonstrated the potential of police data to test theories of DVA and assess police actions. However, there were several limitations in the data, the method for curating the dataset and analysis techniques. The key limitations that should be considered in any interpretation of the findings and in future analysis are considered here.

6.4.1. Limitations of the data

There are limitations to all DVA research DVA that uses police data. Police data only include cases that are reported to the police. Most DVA is not reported to the police (ONS, 2018a); therefore, it is probable that not all events per victim/dyad were included. The repetition estimates in the curated dataset are likely to be an underestimate of the true level of repetition for victims/dyads in the sample. Furthermore, the study uses data from one police force, thus events that were recorded by other forces are not captured in the measure of repetition[8], and specific journeys in a DVA trajectory e.g. the movement of victims when trying to escape DVA (see Bowstead, 2015; 2017) may be missed.

As the data are likely to be an underestimate of repetition, the trajectories of escalation produced in the analyses are likely to be a snapshot of the DVA series between a dyad, rather than a complete trajectory. The trajectories were tested against several hypotheses of the number and shape of DVA trajectories taken from existing literature, namely Walby and Towers (2018), Johnson (2008) and Nagin and Land (1993). The analysis found no evidence of these theories in the curated dataset. Previous research suggests that the DVA patterns that come to police attention differ to those found in other data sources, such as survey data (see Johnson). The patterns in the dataset may therefore not be comparable to the findings of analysis using other data sources. For instance, Walby and Towers' focused on patterns of DVA in the CSEW, and Johnson argued that escalating trajectories are most likely to be found in police data whilst the stable and less frequent/serious trajectories are likely to be found in survey data.

There are limitations to the specific data sources that were selected to be included in the curated dataset. Firstly, the data selected were based on the researcher's observations and interactions with the police force, and a specific four data sources that had been observed were selected. There are other data sources that were observed and not selected, such as BWV footage, victim statements and MARAC referrals, and data sources that were not observed nor selected, such as DVDS referrals, that may have contributed more information. The researcher was also limited to the data that were accessible on the information systems to which they had been granted access, and there may have been additional data sources within information systems that the researcher did not have access to. The selected data sources determined the available information on types of police action, and thus

[8] With the exception of a small number of cases (n=5) in the curated dataset that were recorded by another police force or agency and shared with the police force under study due to the victim residing within the force area.

the available measures were limited and did not account for the many other actions that the police and CJS may take.

Additionally, although the selected data provided more information on victims/perpetrators/events/police action than the original police datasets, the data are still subject to police recording errors. Furthermore, as much of the data was free-text, the quantity and quality of information was variable and led to lots of missing data in the curated dataset. Though the inconsistency of information recording was a limitation, it is recognised that the data were recorded for operational policing purposes and not to test theories of DVA or to evaluate police actions and interventions.

6.4.1.1. Future research

There are several considerations for further research. The first area would be the improvement of police data collection following the measurement framework and criteria for future police data collection. With an improved data collection system, future research may examine whether the revision of police data collection enables the extraction of data that contains all information in the measurement framework as one quantitative dataset that facilitates the analysis of DVA and police action. The second area would be the curation of a dataset using additional sources of CJS data that were not included in this analysis, to determine what information could be extracted from sources such as BWV footage, DVDS and court data to measure DVA repetition and police action. A final suggested area for future research based on the limitations of the data used in this study would be to expand the research to include data from multiple police forces and other agencies to produce a more accurate analysis of DVA patterns and to evaluate the impact of interventions when the interventions of other agencies are accounted for (see Hoyle and Sanders, 2000).

6.4.2. Limitations of the curated dataset

The dataset was built through manual recoding of police data into a set of developed numeric and categorical variables. All manual recoding was done by the researcher. This included the iterative development of the variables and coding scheme, the reading of multiple data sources for over 300 cases, the de-identification of all case files, and the manual coding and data input of information into a new dataset. The manual recoding of information from multiple data sources into the required dataset was extensive and time-consuming. Due to the long process of producing the dataset and the time limits of the study, the curated dataset has a much smaller sample size than existing police datasets, with 325 events, 68 victims and 94 perpetrators. The small sample size reduced the statistical power to detect an effect between the variables included in the analysis and increased the margin of error in the analysis. The small sample size may have contributed to the non-significant results found in the analyses. The sample size may also have contributed to the findings of the trajectory analysis, which did not correspond with findings of previous research, and could not identify patterns of severity escalation.

Furthermore, as all recoding was completed by one researcher, the decisions made e.g. the categorisation of non-crimed events, may have been subject to researcher biases. The coding of information into the curated dataset was not corroborated with other researchers or the police force.

A final limitation to the method of the curated dataset is that the sampling technique does not trace perpetrators through force systems. The dataset facilitated analysis of repeat victims and dyads, though could not focus analysis on repeat perpetrators as not all events relating to each perpetrator were extracted. Analysis therefore could not consider changes in repeat offending overtime outside of a specific dyad.

6.4.2.1. Future research

To increase the size of the dataset, future research may use sophisticated statistical techniques such as natural language processing to speed up the process of identifying and extracting information from free-text. The measurement framework provided by this thesis provides a template coding framework that could be applied to statistical techniques. Furthermore, future research should increase the size of the research team to speed up data extraction and contribute towards the production of a larger dataset that facilitates statistical analysis. Additionally, a larger research team would enable the recoding decisions to be corroborated. Having multiple researchers independently read and code a sample of information would enable the inter-reliability of the coding to be tested and improved.

On the sampling technique, future research would consider following both victim and perpetrator through police systems to enable separate analyses of repeat victimisation and offending over time. Having both victim and perpetrator trajectories in the data would improve the comparability to previous research in this area, for instance the trajectories suggested by criminal careers research (see Nagin and Land, 1993) and the patterns of offender escalation found by Barnham et al (2017).

6.4.3. Limitations of the analysis

The key limitation of the analysis is the size of the dataset, as the small sample size reduced the statistical power and may have contributed to the non-significant findings throughout the analysis.

Another limitation that may have contributed to the non-significant findings was that the analysis did not account for interactions between explanatory variables where interrelationships exist. For instance, Myhill (2019) found that officers are more likely to make an arrest when the event involved physical assault and injury due to perceptions of risk and CPS evidence thresholds (Barlow et al, 2020). Hoyle and Sanders (2000) suggested that the impact of actions such as arrest on DVA repetition vary depending on whether additional interventions are included, specifically specialist support for victims. Hoyle (1998) found that officers were less likely to arrest if they suspected that the victim would not support prosecution. The lack of analysis of these interactions may partially explain the lack of significance between some police actions and DVA repetition. Future analysis should account for possible interactions between these measures when considering the impact of police actions on DVA repetition. Furthermore, the police actions included in this analysis were limited by the available information in the selected data. Other actions and interventions within the police and CJS response such as prosecution and offender programmes should be built into future analysis.

Another key drawback in the measurement of police action and repeat DVA is that the analysis only considered whether the dyad had ever experienced a specific police action at any point in their trajectory[9]. The analysis did not specify at what point in the trajectory the police action was implemented, nor did the analysis specify how many times the action was implemented. As the analysis did not account for when in the trajectory the action took place, the direction of the relationship between police action and the frequency and severity of DVA could not be established.

6.4.3.1. Future research

Future research would repeat this analysis on a much larger dataset. Future research would retest the findings and determine whether the non-significant results, as well as significant findings between police action and DVA repetition and the shape and number of trajectories identified, were a result of the small sample size or were representative of the patterns of DVA and police action in police data.

To develop the analysis and draw more reliable conclusions on the impact of police action on DVA repetition, future analysis would account for interactions between variables. Such interactions may include those between physical assault and arrest (Myhill, 2019) and between arrest and specialist support interventions (Hoyle and Sanders, 2000). Furthermore, future analysis would account for the

[9] Excluding variables of police action that have multiple options i.e. response grading, risk classification and crime status which are measured as the type of action implemented in the first recorded event for each dyad.

number of times an intervention took place as well as the points within a dyad trajectory that interventions took place.

6.5. Conclusion

This chapter discusses the findings of the two results chapters in relation to the research questions and existing literature. The methodological findings show that although the police collect lots of data, the use of multiple information systems and inconsistent recording practices make the data unable to measure DVA repetition. Furthermore, the structure of police data means much of the information that is required for evaluating the influence of police action is not readily extractable. Police data in their current form therefore cannot measure DVA repetition and police action.

From the literature on DVA and policing and insight into police data and information systems, a measurement framework was derived to guide the restructure of police data into a form that can measure DVA repetition. Observations of the police led to a mapping of the police response and identified alternative sources of police data to contribute towards measurement of repeat DVA and police action. To yield the information from police data and enable a measurement tool for analysis, a new dataset was curated that combined and manually derived the required variables from multiple data sources. The dataset provided a tool for statistical analysis, to test the suitability of restructured police data to measure DVA repetition and assess any effects of police actions. A series of statistical analyses were conducted to examine patterns of DVA in the curated dataset and any relationships between specific police actions and DVA repetition. The results of these analyses were discussed in this chapter, though the primary purpose of the analyses was to demonstrate the potential of police data.

The thesis has several implications for police policy and practice, and for DVA theory. The key outputs include a map of the police response to visually demonstrate the complexity of the response and highlight areas of data collection, which may show areas of duplicate data recording that could be combined. Another key output is a measurement framework for collecting and analysis data on DVA. The measurement framework summarises the information required to measure DVA repetition and evaluate police actions. The framework has been embedded into a set of criteria for future data collection. The criteria recommend revisions to data collection processes to enable these data to be routinely available and extractable. The benefits of having these data readily available are both to research and police practice. Extractable data on repeat DVA and police action could facilitate further research on DVA and the effectiveness of police response that could test existing theories of DVA, and inform future police practice. For police practice, having these data readily available could provide vital information to police officers and agencies that could inform the safeguarding and investigative actions taken in response to reported DVA.

The thesis also provided a new and unique methodology for restructuring police data into a form that enables the measurement of DVA and police action. If this methodology was to be expanded to produce much larger datasets, more robust statistical analyses could be conducted to answer specific questions on the relationship between actions taken by the police and partner agencies and the events, victims and perpetrators of DVA that come to police attention. Answering these questions could lead to more evidence-based police responses to DVA that have positive effects on the prevention of further violence and safeguard victims. This new methodology is therefore of interest to both police forces conducting their own research in-house and academics.

7. Conclusion

DVA is a violent crime (Walby and Towers, 2018), and is cause and consequence of inequality (Walby, 2009). DVA is a key source of demand for police forces in England and Wales (HMIC, 2014b), and forces are under great pressure to respond effectively to demand whilst managing stretched resources (Palmer et al, 2019). DVA is repetitive (Walby et al, 2017), thus much of the demand related to DVA that the police receive is accounted for by the same perpetrators and victims (Sherman, 2007; Bland and Ariel, 2015; Barnham et al, 2017). Theories of DVA have implications for legislation and policy, as demonstrated by the introduction of the Controlling and Coercive Behaviour offence (Home Office, 2015) following Stark's (2007) influential conceptualisation of coercive control. Research into the effectiveness of interventions for DVA reduction can have significant effect on police and practice, for instance the introduction of mandatory arrest policies following Sherman and Berk's (1984) influential study on the effects of arrest on DVA recidivism. As theories of DVA and DVA prevention influence policy and practice and therefore the actions experienced by victims and perpetrators, the existing theories need to be regularly and robustly tested. The problems in understanding police demand, evaluating the effectiveness of police actions and testing theories of DVA are largely attributable to measurement.

To propose an effective intervention for DVA requires understanding of its causes and characteristics (Dobash and Dobash, 1979). To understand patterns of DVA require that it is accurately measured (Buzawa and Buzawa, 2003; Walby et al, 2017). HMIC inspections of police forces in England and Wales have consistently raised issues over the quality of police data. HMIC (2017) in their annual report on policing found that whilst the police collect lots of information, much of the data is recorded in various formats across multiple complex information systems, making the data inaccessible, therefore redundant. Concerns have also been raised specifically on the police measurement of DVA. The original inspection of the police response to DVA found that the response was being negatively impacted by data and measurement issues, including ambiguous and multiple DVA definitions, in particular definitions of repeat DVA, and poor quality and quantity of data on DVA (HMIC, 2014b). The most recent report into the state of policing found outdated police information systems were still preventing the identification of repeat victims, thus preventing the measurement of and tailored response to patterns of DVA (HMICFRS, 2019). Poor data and information systems prevents vital information reaching practitioners, and thus puts the safety of the public at risk (HMIC, 2017).

The aim of this thesis was to consider how police data could be improved to enable the measurement of repeat DVA and assess the impact of actions taken by the police. The thesis had three main research questions.

What data do the police have on DVA?

What are the problems with the current structure of police data for measuring DVA repetition?

How can police data be improved to measure DVA repetition?

The previous Discussion chapter revisited the research questions and reviewed the methods that were taken to address the questions, the results of the analyses and the implications of these results in relation to the thesis questions and to the existing literature. This final Conclusion chapter looks at each of the main questions in turn and presents how the thesis has addressed this question. The chapter finishes with the key contributions to police policy, practice and academic theory.

7.1. What data do the police have on DVA?

The first question intended to investigate what forms of data the police already have on DVA. As discussed in the Literature Review, often the quantitative data sources used to report on DVA from police data are PRC (Loveday, 2000) and/or incident data (ONS, 2019a). These data provided limited insight into the characteristics of victims, perpetrators, circumstances of events and police actions. The start of the project intended to identify more sources of data that could be extracted and contribute to statistical analysis of repeat DVA and police action. Observations of the police response and interactions with the force identified appropriate data sources. The data sources were contextualised by mapping out the response and highlighting points of data collection. As is discussed beneath the subsequent research question, four quantitative datasets were extracted and made available for analysis and were found to be unsuitable for measuring DVA repetition and police action. Alternative data sources were therefore considered. The police response and available data are summarised here.

When a report is made to the police, a force call-handler will open an Incident Report to take details of the event. The Incident Report is shared within Command and Control and attending frontline police officers. Frontline officers update the Incident Report. The Incident Report is comprised of standard fields and free-text. Frontline officers wear BWV, which captures the event on video. Whilst at the scene, officers will take victim/witness statements using free-text. For DVA they also complete a DASH with the victim, which is recorded as standard fields for each of the 27 risk assessment questions, and free-text for any additional details added by the officer. If the event crosses the criminal threshold, the police submit a Crime Report. The Crime Report and all evidence collected by the police, including the victim/witness statements and BWV footage, may be shared with CID to pursue an investigation. From CID, the evidence is developed and may be shared with the CPS for a charging decision. After any DVA event, frontline officers should submit a DA referral. The referral is shared with MASH to facilitate safeguarding for the victim. MASH share the referral with relevant agencies such as probation and IDVA, and may refer the case to MARAC. The information entered into the referral by the police, MASH and any other agencies is largely free-text and non-standardised, thus the quantity and quality of information can vary widely. Prior to MARAC, a MARAC report is produced that summarises the event and the history between the victim and perpetrator to share at the MARAC meeting. At MARAC, all agencies involved will share the information they have on the dyad.

The police collect lots of data when responding to DVA. There are therefore several more data sources available to examine the cases of DVA that come to police attention and to measure police activity than those that are typically used in official figures and research (Loveday, 2000; ONS, 2019a). Though there are multiple data sources, the data are collected in various formats by different personnel across multiple systems. The data are therefore not structured into a measurement framework suitable for measuring DVA repetition and assessing the impact of any police actions on DVA repetition.

A measurement framework to measure DVA repetition and police action was derived from the existing literature on DVA presented in the Literature Review, and knowledge of police data and information systems gained from interactions with the force. The framework is in Table 4.1, and shows the measures needed on DVA events, victims, perpetrators and police action to measure patterns of DVA repetition and to consider the impact of police action. The following research question outlines the main problems in the existing structure of police data that prevent the measurement of DVA repetition and police action.

7.2. What are the problems with the current structure of police data for measuring DVA repetition?

The police collect lots of data in various formats across multiple systems. Some of the main data sources used throughout the response to DVA such as incident reports, crime reports and DASH include standard fields. Standard fields refers to information that is expected to be recorded in a standardised numeric or categorical format. As this information is recorded in standard fields, the data can be extracted directly from systems in a quantitative format. At the start of research project, four quantitative datasets were extracted from force systems relating to crime, offenders, incidents and DASH. Exploratory statistical analysis of these data found the existing police datasets unsuitable to measure DVA repetition or evaluate police action. Four key issues were identified with existing police datasets.

The first issue with existing police datasets is the different units of measurement. To measure DVA repetition requires that the data have the event, victim and perpetrator as units of measurement (Walby et al, 2017). The datasets did not consistently record information on victim and perpetrator, therefore the same individuals could not be matched across datasets and repetition could not be measured.

The second issue was the inconsistent recording of personal details. When victims and perpetrators are recorded in the data, the personal details need to be recorded accurately and consistently to match the same individuals within the data and capture repetition (Brimicombe, 2016). In the existing police datasets, personal details such as names, DOBs and addresses were often recorded inconsistently, with lots of missing data and variations of spelling. As personal details could not consistently be matched, any measure of repetition is likely to be inaccurate.

The third issue was the use of multiple DVA markers to identify DVA, and the misuse of DVA markers. Exploratory examination of the events flagged as DVA in the existing crime and incident data found multiple flags and codes in use to identify DVA, including the standard DVA flag for all DVA crimes, as required by the Home Office, and both 'domestic abuse' and 'domestic incident' flags being used to identify DVA in incidents. In addition to flags, incident data relies on incident codes to categorise events. There are a wide variety of incident codes that DVA may be recorded under, in addition to two specific 'domestic incident' and 'domestic crime' codes. Furthermore, though not required at the time of data collection, the Home Office now require that police forces add an additional repeat flag to DVA-flagged crimes that fit the Home Office's definition of repeat DVA (Home Office, 2020a). If different flags are applied inconsistently, then each will extract a different though overlapping sample of DVA. The multiplicity of the available DVA flags adds complexity and confusion to police data recording. Furthermore, exploratory analysis of the flagged crimes found that flags were being applied to events that did not match the definition of DVA. For instance, an assault against a PC when responding to a DVA-related event does not fit the DVA definition as the PC is not the victim of DVA, though several assaults against constables appeared in the police extracted DVA crime data. Events such as this are more likely to be singular than repeat events, therefore having several misclassified single events in the DVA data will affect the overall measure of DVA repetition, and may affect interpretations of relationships between police action and DVA.

The final issue identified in the existing police datasets is that additional information that could contribute towards understandings of DVA and police action though was lost in free-text narratives written by officers and agencies. Free-text often provided additional information that could help to identify and understand patterns of repeat DVA and any association between action taken by the police and DVA repetition.

As the datasets were deemed unsuitable in their current format, alternative data were sought, using information from observations and the map of the police response process. A new quantitative dataset was curated using alternative data sources to demonstrate the potential of police data when reconstructed into a suitable measurement framework. The alternative data sources included crime reports, incident reports and DASH, though included the free-text fields of these data sources as well as the standard fields. The new data source added was the DA referral, which is the referral made by the police force to MASH for all cases of DVA. The referral is largely free-text and provides MASH with a free-text summary of the event written by the responding police officer. The referral is then reviewed by MASH and populated with information on the victim, perpetrator and event to facilitate an appropriate safeguarding plan. The referral thus provides an ideal site of data, as the referrals should be available for all DVA events therefore capturing repetition, and contain detailed information on victims, perpetrators and police action. However, the free-text format of the referral as well as the free-text components of other data sources means that key information is not readily extractable.

The data from each source were therefore individually and manually reconstructed into a quantitative dataset that enabled statistical analysis. The referral provided the base source of data for the dataset, and information from the other data sources were added. The manual reconstruction of data was an extensive and time-consuming process. Due to the time taken to restructure the data into a suitable form, the curated dataset has a relatively small sample size. A series of analyses on the dataset demonstrated how police data could be used to measure patterns of DVA and assess the impact of police action.

7.3. How can police data be improved to measure DVA repetition?

Though the curated dataset has a small sample size, statistical analyses demonstrated that the ability of police data to measure DVA repetition and assess police action could be improved if police data were structured following the measurement framework. The curated dataset increased the measure of DVA repetition to 51%, based on the percentage of repeat victims, compared to 21% in the existing police recorded crime data. The curated dataset also captured forms of police action that are a key part of the response though are often not included in analysis of police action, such as information sharing with other agencies. As the dataset had a greater capture of repetition and information on victims, perpetrators, events and police action, the dataset could test theories of DVA and assess the impact of police action if produced on a much larger scale. The main purpose of the analysis was to demonstrate the potential of police data and not to draw sound conclusions on patterns of repeat DVA or the effect of police action on DVA repetition, though the results highlight areas for further testing and investigation, summarised in the subsequent contributions of the thesis.

From the review of police data, the curation and analysis of the curated dataset, a set of criteria for future police data collection was derived, presented in Table 4.3. The criteria state that the collection of data by police for DVA should follow the measurement framework set out by the thesis. The criteria then address each of the issues identified in existing police datasets. Firstly, to measure repetition, any data need to include units of measurement on the event, victim and perpetrator. The data on events, victims and perpetrators should be stored within one system. This would enable data to be extracted as one dataset, allow victims and perpetrators to be included in the same analysis and reduce the need to extract multiple datasets. If data are stored across multiple systems, then each individual should be allocated a unique identifier. The identifier should be numeric and not contain any of the individual's personal details, so that the identifier does not need to change if/when personal details change. To identify DVA should rely on DVA flags for both crimes and incidents. Incident codes should summarise event circumstances, whilst the flag distinguishes the event as DVA. Only one flag should be attached. The flag should only be attached to events that meet the DVA definition (Home Office, 2020a), thus police forces should be sufficiently trained to understand and identify cases that meet this definition. Regarding free-text, if police data collection was designed following the measurement framework, some of the information embedded within the free-text could be replaced with standard fields. However, the inclusion of more standard fields should not completely replace the free-text written by responding officers. Free-text narratives provide valuable insight into the complexity of DVA, and there should be space to retain some free-text in police data.

7.4. Key contributions

The thesis has several key contributions to police policy, practice and theory. To EBP, the first contribution is a measurement framework for collecting data on DVA. The analysis demonstrated that structuring police data using the derived measurement framework enables the testing of DVA theories and assessment of any impact of police actions on DVA repetition. Theories of DVA and prevention have implications for policy and practice, therefore implications for the intervention and safeguarding measures experienced by victims and perpetrators. It is therefore vital that DVA theories and links between interventions and DVA are robustly tested and the evidence continuously updated. Having police data collected following the measurement framework should increase the availability of information for research into DVA and policing to be conducted in-house by the police, as well as by academics and other agencies, thus contributing to the ongoing progression of EBP.

To EBP the thesis also offers a set of criteria for future police data collection. The improvement of police data would enhance the ability to conduct research that can influence evidence-based practice. In addition to research, having data collection systems revised to follow these criteria could improve the accessibility of data for practitioners responding to DVA. As found consistently in HMIC/HMICFRS (2014b; 2015; 2019) inspections, the complexity of data collection systems across police forces prevents vital information from being shared between practitioners in their response to crime, including DVA, which jeopardises public safety. Following the criteria for future data collection, police forces including Lancashire Constabulary could revise their data collection systems and improve the accessibility and sharing of information to responding practitioners when they need it, allowing them to tailor response and appropriately allocate resources.

For police policy, the recommendation is the development of a specific force policy for the collection, storage and sharing of data relating to DVA, following the measurement framework and criteria for future police data collection. For police practice, the results of the thesis should encourage sufficient training for frontline police officers on the definition and identification of DVA, and should emphasise the importance of accurate and consistent data collection.

The thesis has implications for DVA theory. Improved police data on DVA will enable the testing and revision of existing theories of DVA, demonstrated by the statistical analysis of reconstructed police data. For instance, the analysis found that when frequency as well as prevalence was taken into account, the majority of DVA was against female victims by male perpetrators. This could support DVA theories that indicate most DVA is gender asymmetrical (Dobash and Dobash, 1979; 2004) and that robust measurement is needed to make this gender disparity visible (Bland and Ariel, 2015; Walby et al, 2017). On escalation, the thesis analysis found no evidence of escalating frequency in repeat DVA, contradicting findings of previous research on DVA repetition in police data (Bland and Ariel, 2015; Brimicombe, 2016; Barnham et al, 2017). Due to the limitations of the data and the analysis, these findings are not interpreted to be robust challenges to existing theory, but instead a demonstration of the ability of police data to contribute towards the research that tests and challenges existing theory of DVA. The analyses therefore highlight areas within the DVA and policing literature for further investigation.

Finally, with a new measurement framework for collecting police data and a methodology for restructuring existing police data into this framework, the thesis sets a research agenda to maximise the usability of police data to measure and understand patterns of DVA and evaluate the impact of police actions on DVA repetition. Improving the estimate of repetition and understanding of DVA patterns, as well as knowledge on the impact of police actions, will assist the police in decision-making around risk and the targeting of resources to interrupt and reduce DVA repetition.

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APPENDIX: Curated dataset variables

Name	Coding	Description
Identifiers		
Dyad_id	-	Dyad ID
Victim_id	-	Victim ID
Perp_id	-	Perpetrator ID
Event_id	-	Event ID
Cm_incident_ref	-	Police force incident log number
Referral information		
Referral_date	-	Referral date
Incident_date	-	Incident date
Referring_officer	0. Police Constable 1. Special Constable 2. Police Staff 3. Other	Role of the person submitting the referral
VA_VC	0. No 1. Yes	Has the victim had any previous Vulnerable Adult or Vulnerable Child referrals
External	0. No 1. Yes	Was the event reported by another police force/agency
Simultaneous	0. No 1. Yes	Did the event involve violence from both victim and perpetrator
Counter	0. No 1. Yes	Did the event involve a counter allegation

Name	Coding	Description
Victim information		
No_victimisations_total	-	Number of times victim appears in the dataset
Vic_age	16… N	Age of victim in years
Vic_sex	0. Male 1. Female 2. Other	Sex of victim
Vic_ethnic	0. White 1. Mixed/Multiple ethnic groups 2. Asian/Asian British 3. Black/African/Caribbean/Black British 4. Other ethnic group	Victim ethnicity. ONS (2016) categories.
Vic_language	-	Victim language
Vic_occupation	-	Victim occupation
Vic_socio	1.1. Large employer and higher managerial and administrative occupations 1.2. Higher professional occupations 2. Lower professional and higher technical occupations 3. Intermediate occupations 4. Small employers and own account workers 5. Lower supervisory and technical occupations 6. Semi-routine occupations 7. Routine occupations 8. Never worked and long-term unemployed	Socio-economic classification of victim, taken from occupation field and identified in the ONS NS-SEC Coding Tool. Addition of 9. Student and 10. Retired

Name	Coding	Description
	9. Student *10. Retired* *98. Unemployed* *99. Unknown*	
Vic_employ	0. Unemployed 1. Employed 2. Economically inactive	Victim employment status
Vic_housing	0. Owner Occupier 1. Tenant – private or social 2. In managed residential accommodation (e.g. student accommodation, hospital staff accommodation) 3. No fixed address/homeless/temporary accommodation 4. Living with parents 5. Other (e.g. refuge, prison, hospital)	Victim housing type
LiveWPerp	0. No – not living with perpetrator 1. No – was living with perpetrator at the time of the event but has now left 2. Yes	Is the victim living with the perpetrator
Vic_physhealth	0. No 1. Yes	Does the victim have any physical health problems
Vic_MH	0. No 1. Yes	Does the victim have any mental health problems
Vic_alcohol	0. No 1. Yes	Does the victim have any issues with alcohol use/dependency
Vic_drug	0. No 1. Yes	Does the victim have any issues with substance misuse

Name	Coding	Description
Vic_finance	0. No 1. Yes	Does the victim have any financial issues
Vic_conv	0. No 1. Yes	Does the victim have any previous convictions
Perpetrator information		
No_perps_total	-	Number of times the perpetrator appears in the dataset
Perp_age	16… N	Age of perpetrator in years
Perp_sex	0. Male 1. Female 2. Other	Sex of perpetrator
Perp_ethnic	0. White 1. Mixed/Multiple ethnic groups 2. Asian/Asian British 3. Black/African/Caribbean/Black British 4. Other ethnic group	Perpetrator ethnicity
Perp_language	-	Language spoken by perpetrator.
Perp_alias	0. No 1. Yes	Indicates whether the perpetrator has any known aliases.
Perp_occupation	-	Perpetrator occupation
Perp_socio	1.1. Large employer and higher managerial and administrative occupations 1.2. Higher professional occupations 2. Lower professional and higher technical occupations 3. Intermediate occupations	Socio-economic classification of victim, taken from occupation field and identified in the ONS NS-SEC Coding Tool.

Name	Coding	Description
	4. Small employers and own account workers 5. Lower supervisory and technical occupations 6. Semi-routine occupations 7. Routine occupations 8. Never worked and long-term unemployed *9. Student* *10. Retired* *98. Unemployed* *99. Unknown*	
Perp_employ	0. Unemployed 1. Employed 2. Economically inactive	Perpetrator employment status
Perp_housing	0. Owner Occupier 1. Tenant – private or social 2. In managed residential accommodation (e.g. student accommodation, hospital staff accommodation) 3. No fixed address/homeless/temporary accommodation 4. Living with parents 5. Other (e.g. refuge, prison, hospital)	Perpetrator housing type
Perp_physhealth	0. No 1. Yes	Does the perpetrator have any physical health problems
Perp_MH	0. No 1. Yes	Does the perpetrator have any mental health problems
Perp_alcohol	0. No 1. Yes	Does the perpetrator have any issues with alcohol use/addiction/dependency
Perp_drug	0. No 1. Yes	Does the perpetrator have any issues with substance misuse

Name	Coding	Description
Perp_finance	0. No 1. Yes	Does the perpetrator have any financial issues
PNC	0. No 1. Yes	Was a PNC check completed
Perp_conv	0 …N 98. Convictions but number unknown 99. Unknown due to no PNC check	Number of previous convictions for perpetrator
PND	0. No 1. Yes	Was a PND check completed
Prev_violence	0. No 1. Yes	Does the perpetrator have any convictions for violence
Prev_sex	0. No 1. Yes	Does the perpetrator have any convictions for sexual offences.
Prev_crimdam	0. No 1. Yes	Does the perpetrator have any convictions for criminal damage
Prev_other	0. No 1. Yes	Does the perpetrator have convictions for any other offences
Warning_marker	0. No 1. Yes	Does the perpetrator have any violent or weapons warning marker
Dyad information		
Relationship	0. Partner/Ex 1. Son/Daughter 2. Brother/Sister	Relationship between victim and perpetrator

Name	Coding	Description
	3. Parent 4. Grandparent 5. Other 9. Unknown	
Dyad_refs	-	Total number of referrals per dyad
Prev_MARAC	0. No 1. Yes	Have the dyad been to MARAC
Children_together	0. No 1. Yes	Do the dyad have children/dependents together
Non_Mol	0. No 1. Yes	Is there a non-molestation order in place
Restrain_order	0. No 1. Yes	Is there a restraining order in place
Event information		
Who_report	0. Victim 1. Witness 2. Suspect 3. Victim and suspect 4. Other	Who reported the event to police
Response	1. Emergency response 2. Priority response 3. Planned response 4. Telephone resolution 5. Police report only	What police response grade was allocated
Police_attend	0. No 1. Yes	Did the police attend the scene
Event_loc	0. Home address 1. Outside/near home address 2. Other residential address (friend, relative etc.)	Event location

Name	Coding	Description
	3. Public place (nightclub, street, transport etc.) 4. Other	
No_cm_event	0. Crimed incident 1. Verbal altercation 2. Breach (bail conditions, non-molestation order, restraining order, harassment warning) 3. Threats 4. Stalking 5. Harassment 6. Theft/Unauthorised Taking 7. Criminal Damage 8. Assault without injury 9. Assault with injury 10. Rape 11. Sexual assault/other offences 12. Other	Description code for non-crimed events
Offence	-	Home Office offence type
HO_category	-	Home Office offence category
HOC	-	Home Office crime code.
Flagged	0. No 1. Yes 8. NA	Was the crime flagged as DVA
Harm_a: physical assault no visible injury **Harm_b: physical assault with visible injury** **Harm_c: mental/emotional distress**	0. No 1. Yes	What harm was caused to the victims

Name	Coding	Description
Harm_d: economic/financial loss **Harm_e: other** **Harm_f: unknown**		
Vic_spoken	0. No 1. Yes	Did the police speak to the victim
Perp_present	0. No 1. Yes	Was the perpetrator still at the scene when police attended
Child_present	0. No 1. Yes	Were any children present
Perp_intox	0. No 1. Yes	Was the perpetrator intoxicated
Vic_intox	0. No 1. Yes	Was the victim intoxicated
Witnesses	0. No 1. Yes	Were there any witnesses
Arrest	0. No 1. Yes	Was the perpetrator arrested
DASH_comp	0. No – not complete 1. No – refused by victim 2. Yes 8. NA	Was DASH completed
Injury_a: minor bruising or black eye **Injury_b:** severe bruising **Injury_c:** scratches **Injury_d:** cuts **Injury_e:** puncture or stab wounds **Injury_f:** broken/cracked/fractured bones	0. No 1. Yes 8. No injury received	Did the victim receive a physical injury

Name	Coding	Description
Injury_g: nose bleed **Injury_h:** broken nose **Injury_i:** broken/lost teeth **Injury_j:** chipped teeth **Injury_k:** dislocation of joints **Injury_l:** concussion or loss of consciousness **Injury_m:** internal injuries (e.g. internal bleeding, damage to internal organs) **Injury_n:** facial/head injuries (no mention of bruising) **Injury_o:** eye/facial injuries caused by acid, paint, sand etc. thrown in face **Injury_p:** Other		
Separated:	0. No 1. Yes - separated 2. Yes – tried to separate/separated in past year 3. Non-intimate partner	Are victim and perpetrator separated
Abuse_more:	0. No 1. Yes 8. NA	Has the victim stated the abuse is happening more
Abuse_worse:	0. No 1. Yes	Has the victim stated the abuse is getting worse

Name	Coding	Description
	8. NA	
Ever_weapons	0. No 1. Yes 8. NA	Has the perpetrator ever used weapons against victim
Ever_threat	0. No 1. Yes 8. NA	Has the perpetrator ever threatened to kill victim /someone else
Ever_strangle	0. No 1. Yes 8.NA	Has the perpetrator ever attempted to strangle/choke/suffocate/drown victim
Risk_level	0. Standard 1. Medium 2. High 8. NA	Risk classification
Outcome information		
Refer_agency	0. No 1. Yes	Was the referral shared with other agencies
Agency_1: Probation **Agency_2:** IDVA **Agency_3:** Health **Agency_4**: Mental health **Agency_5:** CART/CSC **Agency_6:** CFW **Agency_7:** ASC	0. No 1. Yes 8. NA	Which organisations was the referral shared with

Name	Coding	Description
Agency_8: Education **Agency_9:** Substance misuse **Agency_10:** Other		
Refer_MARAC	0. No 1. No – referral already pending 2. Yes 8. NA	Was the referral referred to MARAC
Decision_referral	0. NFA 1. Stepped Up 2. Stepped Down 3. Single Agency – Police 4. Single Agency – IDVA 5. Referred to CART 6. Other	Referral decision
Crime_status	0. Undetected 1. Positive outcome 2. Cancelled 3. Positive outcome RJ 4. Prosecution not possible 5. Closed 6. Crime under active investigation 7. Court disposal 8. Police disposal 9. No further action 98. Unknown 99. Non crimed incident	Crime status for crimed events.
Crime _outcome	0. Charge/Summonsed 1. Caution/Youth Caution	Outcome of recorded crimes.

Name	Coding	Description
	2. Taken into Consideration (TIC) 3. Penalty Notice for Disorder (PND) 4. Cannabis Warning 5. Community Resolution 6. Evidential difficulties in proceeding 7. Unable to prosecute offender (e.g. age/health/deceased) 8. Prosecution unlikely to succeed or not in public interest – CPS 9. Prosecution unlikely to succeed or not in public interest – Police 10. Time limit expired 11. Case closed: no line of enquiry 12. Case closed: Systems Thinking Principles Applied 13. Crime remains under active investigation 14. Prosecution not in the public interest (CPS decision) 15. Youth Caution 16. Adult Caution 17. The offender has died 18. Formal action against the offender is not in the public interest (Police decision) 19. Prosecution prevented – named suspect identified but is below the age of criminal responsibility 20. Prosecution prevented – named suspect identified but victim or key witness is dead or too ill to give evidence 21. Evidential difficulties victim based – named suspect not identified	

Name	Coding	Description
	22. Evidential difficulties named suspect identified 23. Evidential difficulties victim based – named suspect identified 24. Prosecution time limit expired 25. Other Agency Delegations 26. Named suspect – further investigation not in public interest 27. Charge/Summonsed with Alternate Offence 28. Youth Caution with Alternate Offence 29. Adult Caution with Alternate Offence 99. Non crimed incident	