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Reducing Repeat Harm: Forecasting high-harm victims for prevention and protection

Submitted in part fulfilment of the

requirements for the

Master's Degree in Applied Criminology and Police Management

2021

Research Contract

This research aims to support the operational targeting of high-harm victims by identifying concentrations of crime count and crime harm. Analysis seeks to establish the survival of these individuals from the high-harm cohort in one period of time to the next to support prediction. Finally, the identification of further patterns in the distribution of crime are sought to enable effective targeting.

Research Questions

The research questions and sub-questions are as follows;

1. **To what extent can the "power few" high-harm victims be predicted based on the history of prior victimisations - and which time period produces the greatest accuracy?**

2.a. Do Kent Police crime records from 2014 to 2019 show annual patterns of concentrations when using the Cambridge Crime Harm Index (CCHI) similar to that demonstrated by Dudfield et al. (2017) in Dorset? Are there similar patterns with respect to crime counts against victims?

2.b. Across all unique persons recorded by Kent Police in 2014,15,16,17,18 & 19, what is the concentration of total CCHI values across a power few of persons for whom the sum of their harm equals or exceeds 10% and 80% of the total and what is the ratio of harm between the PF and NPF? How does this compare for count?

2.c. In calculating the same power few threshold of total harm for victims separately for each year (2014-19) in Kent, how much consistency in the *shape* of the distribution is there across the five years? How does this compare for count?

2.d. What versatility is there in the offence types suffered by PF victims for count and harm?

2.e. What percentage of the victims in the top 10% and 80%-of-CCHI power few in 2014 remain in that high-harm proportion from 2014 to 2015, and from 2014 and 2015 to 2016, through to 2019? How does this compare for count? How does this compare to specific crime types?

2.f. In calculating the same power few threshold of total harm for victims separately for each year (2014-19) in Kent, how much consistency is there in the unique victims in the list of top 100 victims by annual harm total across the five years? How does this compare for count?

2.g. What percentage of victims in the top 10% and 80%-of-CCHI power few in 2014 remains in the high-harm proportion in 2015, 2016, 2017, 2018 and 2019? How does this compare for count?

2.h. Using conditional probability from one time-period to the next, which unit of time provides the greatest accuracy for prediction by count and CCHI; one month, three months, six months or a year?

2.i. What percentage of victims in the 80%-of-CCHI for the six-years suffer an escalation in harm and how many de-escalate? What percentage of these victims suffer repeat escalation?

2.j. For crime count, what is the conditional probability of a victim suffering a further offence given prior victimisations? What is the frequency with which these repeats occur?

2.k. How are high-harm concentrations distributed based on demographic variables? How does this compare to the power few by count?

2.l. Do crimes within the years 2014-2019 evidence a victim-offender overlap (VOO) and what percentage of harm is attributable to the VOO?

2.m. Using the age variable within the crime data, when in the life-course does the VOO occur and what is the consistency of this across the victim-offender population?

Research Design

The primary variable used was prior victimisations, studied using descriptive analysis to identify patterns in the distribution of crime, including survival analysis to support prediction. Varying concentrations of crime and harm are analysed over time and by different units of time to find the optimal level of accuracy for forecasting future harm.

Data

Kent Police crime records were used from 2014 to 2019 with parameters set to ascertain only victim-based crime. After data cleaning, a total of 677,361 records were analysed in the victim dataset and

116,066 in the offender dataset when studying the VOO. For each crime, variables about the crime and individual were included to support analysis of the research questions.

Analytical Methods

Harm scores were embedded into the datasets using the Cambridge Crime Harm Index and then the Power Few were established by rank ordering victim's harm scores and calculating cumulative harm. Different Power Few concentrations were identified and compared to the Non-Power Few, before being repeated for crime count. The versatility of the Power Few was analysed across crime types using pivot tables to establish the proportion of victims suffering only one offence, single category offences or offences across crime types.

Survival analysis was then conducted on the different Power Few concentrations using different units of time with excel formulas, predominantly 'COUNTIF', to establish the accuracy of forecasting. Specificity and sensitivity analyses were conducted to establish the accuracy of prediction. Escalation within the Power Few was analysed using Excel formulas to determine the predictability of repeat escalation and the conditional probability and frequency of repeat victimisation was analysed.

Power Few concentrations were analysed against age and gender and victim-offenders were analysed to establish Power Few concentrations using the methodology outlined above. The victim-offender overlap onset age was analysed against victim and offender age-crime curves from the respective datasets.

Findings

Consistent Power Few concentrations were identified with between 0.23% and 0.38% of victims suffering 10% of all harm and between 12.93% and 15.15% suffering 80% of total harm. Crime was not as concentrated when analysing count, however Power Few distributions were still evident. The Power Few suffered disproportionate levels of both crime and harm with a harm ratio of up 47:1

compared to the Non-Power Few. Survival analysis illustrated that years were the optimal unit of time for predictive accuracy, however survival in the Power Few year-to-year was less than 10%. Analysing the Power Few did, however, lead to an almost 40% positive prediction value in terms of those who went on to be a victim, with a mean harm ratio compared to the Non-Power Few of 11:1.

Over 35% of the Power Few (harm) cohort suffered only one offence with the remaining majority suffering across crime types. The Power Few (Count) followed a similar pattern. Escalation was found to be rare, however, the conditional probability analysis demonstrated that after three repeats, a victim is more likely than not to suffer another offence. Repeats tend to occur with increasing frequency after each consecutive repeat with 9.8% of first repeats occurring within 14 days.

A greater proportion of the Power Few were females who suffered higher mean harm than males, and the Power Few were concentrated in greater numbers in the teenage years compared to the Non-Power Few. Victim-offenders who were in both the victim and offender Power Few cohorts accounted for 0.51% of the combined victim and offender datasets. These Victim-Offender Power Few have substantial concentrations of harm attributable to them, which is replicated less severely when analysing crime count. The VOO onset age showed a skewed distribution to the late teenage years that follows the offender age-crime curve.

Policy Implications

This research has identified that Power Few concentrations should be targeted given the proportion that go on to suffer higher harm scores than the Non-Power Few in the subsequent year. Furthermore, targeting victims based on the number of repeats they suffer could be embedded into a repeat victim policy with parameters set around timeliness of a policing response. Further survival analysis should be conducted on the VOO and a multivariate analysis should be conducted seeking to improve the accuracy of prediction.

Acknowledgements

Firstly, I would like to thank Dr Barak Ariel for all of his support, guidance and wisdom, and for always providing reassurance; it has helped me navigate my way through this journey. I would also like to thank both Kent McFadzien and Vincent Harinam for their constant counsel and support with both my data and the associated analysis.

I am very thankful to the Chief Officer team at Kent Police for their support in this endeavour and providing me access to the right people to enable this research, I am truly appreciative of the help. My gratitude extends to both Nicola Endacott and Gary Beautridge at Kent Police for their respective advice in securing and understanding the data, and operationalising this research going forward.

Finally, none of this would have been possible without the endless patience, understanding and support of my wife, Jo and sons Arthur and George, who regularly heard me mumbling about data issues and suffered last minute changes to plans where I needed to work on my analysis. This thanks also extends to my wider family for their constant encouragement and support.

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1. Introduction

1.1. Context

Can the police accurately forecast re-victimisation? The purpose of this thesis is to examine to what extent harm suffered by victims in Kent can predict future harm suffered by those individuals. Descriptive analysis of the distributions, patterns and concentrations of victim harm will be conducted against victim crime records spanning six years. This will be supported by survival analysis over different periods of time and using different harm concentrations to establish how accurately high-harm targets can be forecast to support harm prevention.

A 'victim' is defined as 'a person harmed by a crime, tort or other wrong' (Black's Law Dictionary 2009). Harm is felt most by the victims themselves, which is partly why they are the focus of this research, as opposed to offenders or places where crime occurs. A comprehensive review shows that the harm suffered by victims is extensive and includes shock, guilt, loss of faith in society, physical injury, financial loss, anger, fear, depression and making changes to lifestyle (Shapland and Hall 2007). In addition to harm, the costs of crime are extensive, including security expenditure, insurance and expenses on victim, health and criminal justice services (Brand and Price 2000). Preventing the consequences of crime is therefore vital.

Prevention is better than cure (Royal College of Nursing 2021). The effectiveness of a police force can be demonstrated by preventing crime. Solving a crime after the event means the harm has already been done to the victim. Similarly, the low conversion rate of crime to 'positive outcomes' consequently impacts the ability to manage offenders through rehabilitation and desistance, or incapacitation. Nationally, in 2019/20 only 10.8% of offences had a recognised formal positive sanction such as a charge, caution or penalty notice for disorder; meaning that known offenders represent a smaller targetable sample than known victims (Home Office 2020a). In addition, legal and political support for victims is strong, with the new Domestic Abuse Act 2021 having been passed and a new 'Victims Law' under consideration (HM Government 18.05.2021; 2018).

Evidence also suggests that poor responses to victimisation and ineffectiveness can undermine legitimacy and public trust and confidence (Bell 2016; Tankebe 2013). Protecting victims by preventing harm is intrinsic to public service, underpinning police legitimacy and promoting the model of policing by consent, which is indicative of a police *service* over a police *force* (Bottoms and Tankebe 2017; Tyler 2017). Police protection is especially pertinent to vulnerable victims, some of whom may not have an 'internal locus of control' which would otherwise enable them to protect themselves from harm (Pease 2008). This research aims to support an effective and legitimate evidence-based policing response by developing a better targeting approach with a view to reducing harm. Evidence-based policing advocates using the most valid evidence for practice (Sherman 1998).

1.2. Making Change

Kent Police manage and track repeat callers and also conduct analysis on repeat domestic abuse cases on the basis of the number of incidents. The force maintains a strong victim focus in respect of safeguarding and support, and maintains a comprehensive understanding of the degree of vulnerability within Kent (HMICFRS 2019a). That said, the force has a strong multi-faceted offender-focus and employs numerous proactive targeting strategies, for example through intelligence-led investigations into organised crime groups. By comparison, victim-based targeting is currently dependent on officer judgement or partner-agency referrals. Opportunities exist to improve this approach by understanding the distribution of harm to identify targets for intervention.

Kent Police could potentially enhance its *targeting* strategy by understanding the association between prior victimisation and future victimisation to identify and protect repeat victims. Sherman (1992) advocates epidemiological crime-control research to examine the differences, distributions, patterns and concentrations of crime to identify high-risk targets that represent the optimal 'yield' by establishing where the greatest risk of future crime will be. This dissertation presents analysis to identify high-harm victim concentrations in order to try and accurately predict future re-victimisation. The research focuses on identifying feasible targets with sufficient accuracy to enable police forces to operationalise interventions to optimise reductions in repeat-victimisation (Sherman 1992).

1.3. The Research

This research uses six years of police crime data to try and better understand some of the longitudinal patterns of victim harm and crime, as well as measure predictability over time. This characteristic of the design also enables replication of the analysis over periods of time. To this end, the key research question is:

> **To what extent can the "power few" high-harm victims be predicted based on the history of prior victimisations - and which time period produces the greatest accuracy?**

A further thirteen sub-questions focusing on four broad areas of analysis were then set up to assess the potential of prediction using police records: (a) the compilation and consistency of concentrations of harm and crime over time; (b) the survival of victims within these concentrations from one period of time to the next; (c) patterns within the data including conditional probability of repeat victimisation, frequency, escalation, versatility and variance by demographic variables; and (d) the existence of the victim-offender overlap. The overarching purpose of the research is to enable prioritisation for enhanced intervention based on harm (Sherman 2019).

1.4. A Roadmap to the Dissertation

This dissertation provides a structured breakdown of the relevant literature including the current theory, supporting empirical evidence and opportunities for exploratory research. A methodology chapter details the design, data, analytical techniques and commentary on external validity. The next chapter documents the findings set against the research questions, employing measures of central tendency to describe the patterns within the data with statistical tests completed as required. A chapter is then dedicated to a discussion of the findings, policy implications, relevance to the existing literature and limitations of this research. A final chapter then draws conclusions of this work and sets recommendations looking forward.

2. Literature Review

Can the police accurately target victimisation using police records? To answer this question, an understanding of the distributions, patterns and concentrations of victimisation are needed. These concentrations can be *targeted*, using *tested* practices that are *tracked* with regards to implementation and outcomes; part of a Triple-T evidence-based policing approach (Sherman 2013). By proactively using evidence to complement conventional police tradecraft and move beyond 'random patrol, rapid response and reactive investigation', the police can be more effective at preventing harm (Sherman 2013; Sherman 2015). The prevention of crime and disorder through the design of long-term evidence-based policing methods is advocated by HMICFRS as a good measure for determining police success (HMICFRS 2020).

In light of this, police performance measures currently lack accountability for reducing repeat victimisation *per se.* The College of Policing limits discussion on repeat victimisation to hate crime, the Home Office Annual Data Requirement omits any reporting on the identification or tackling of repeat victimisation, and the Office of National Statistics does not publish any data on the subject (College of Policing 20.10.2020; DataPoliceUK n.d.; ONS 15.05.2021). Only now are HMICFRS proposing to inspect against this as a measure of performance as part of the PEEL Assessment Framework 2021/22 (HMICFRS 09.04.2021). Developing this understanding to support targeting is therefore central to this research.

This literature review explores the theory and core concepts of victimisation and repeat victimisation before focusing more precisely on the concept of harm and concentrations of harm. These two concepts – crime counts and crime harm – are pertinent because they can differ in measurement, patterns of distribution and policy implications. These two approaches for targeting victims are considered in the subsequent section, before discussing the ability to forecast harm. The final section covers an appraisal of the victim-offender overlap (VOO), representing a greater concentration of crime that could be targeted to maximise the yield from preventative strategies.

2.1. Theories of Victimisation

This subchapter provides a brief overview of the history of victimisation theories before exploring lifestyle theory, rational choice theory and the relevance of demographic factors. A review of theories by Burgess et al. (2013) illustrates the evolution from classical theory through to current modern theories that are victim-based, interactive or societal. Victim-based theory included early victim typologies, interactive theory includes Rationale Choice Theory and 'risky lifestyles', and societal focusses on social mechanisms that accommodate vulnerability (Burgess et al. 2013). As a starting point, the concept of 'victims' has been developed over decades, with Von Hentig (1940) categorising murder victims into typologies, for example, the wanton or depressive. Further developments included the actions of victims being considered as triggers for crime, before more subtle links were made to indirect actions by victims themselves such as failing to secure property or associating with offenders (Wolfgang 1958; Miethe and Meier 1994).

A more holistic theory is the 'Lifestyle/Exposure Model of Personal Victimisation', which shows that routine activities within one's lifestyle can lead to direct exposure to victimisation, or exposure via criminal associations who share the same characteristics (Hindelang et al. 1978, p. 243; Pratt and Turanovic 2015). Lifestyle can be predicated on how people adjust to structural constraints and role expectations, and to what extent these constraints *allow* people to adjust, which directly impacts risk of victimisation (Turanovic et al. 2016). Similarly, specific lifestyle-related characteristics correlate to the probability of victimisation, including income, marital status, and ethnicity (Cohen and Felson 1979). Gale and Coupe (2005) identified that combining predictors led to more precision, with both age and gender linked to the likelihood of being a robbery victim; an important point when considering prediction. A key trait is the ability to exercise self-control, as this can lead a victim to make changes to their risky lifestyle, which in turn is linked to the likelihood of further victimisation (Turanovic and Pratt 2014).

A further related theory is Rational Choice Theory which is a complementary theory to Routine Activities Theory, with the former including a description of offender decision-making (Tillyer 2011). Routine Activity Theory dictates that predominantly, for a crime to occur there needs to be spatiotemporal convergence of 'suitable targets' or victims, 'motivated offenders' and a lack of 'capable guardians' (Cohen and Felson 1979). Individuals' *routine* activities can be linked to victimisation, for example young persons engaged in peer group activity, as opposed to being with family, are more likely to be victimised (Cohen and Felson 1979). Rational Choice Theory further explains that an offender will choose the easiest target for lowest risk and with the highest reward (Miethe and Meier 1994; Cornish and Clarke 1986 cited in Coupe 2017).

Gottfredson (1981) theorised that the traditional macro-view of characteristics and lifestyle, should be complemented with the micro-view, namely specific activities within lifestyle that enhance someone's 'victim proneness'. Research of this nature has been conducted and shown for example, that specific lifestyle characteristics predictive of single sexual offence victims are also predictive factors for recurrent victims (Fisher et al. 2009). Victim demographic characteristics have also been studied in relation to crime clearance rates and identified that whilst race saw no statistically significant difference, age and gender showed a difference for some crime types (Roberts 2008). Demographic characteristics are important as they may correlate with certain types of behaviour such as excessive drinking, that may increase risk (Pratt and Turanovic 2015). Empirical support for this notion has been broadened to show interaction and correlations between personal characteristics and spatial variations in crime (Tseloni and Pease 2014).

2.2. Repeat Victimisation

Repeat victimisation occurs when victims suffer multiple crimes over a specific time-period (Pease and Farrell 2016). Whilst crime prevalence; the proportion of the population who are victimised, and crime incidence; the number of crimes per thousand population, are important from a trust and confidence perspective; crime concentration, which counts the number of crimes per victim, identifies potential victims to target resources on (Farrell 1995; Pease and Farrell 1993). The best predictor of further victimisation is prior victimisation, with one study establishing that the likelihood of further victimisation after the first, increased four-fold (Forrester et al. 1988). The extent of repeat victimisation has sometimes been underestimated through police recording practices, however the Crime Survey for England and Wales, has shown that repeat victimisation has previously accounted for 39% of crime (Ignatans and Pease 2016; 2018).

This next section reviews literature regarding escalation of harm across the course of repeat victimisation, followed by research on intermittency between repeats. The final section then touches on the overlap with other concepts such as concentrations of crime. Firstly, recent evidence has shown that escalation in the severity of the harm is rare across domestic abuse dyads (Bland and Ariel 2015; Kerr et al. 2017). A review across four forces evidenced that there was not a significant pattern of escalating seriousness over time and that first offences are predominantly the most serious (Bland and Ariel 2020). Research in Thames Valley found that a small group of highest-harm victims evidenced no escalation in severity over time but did find an increased frequency in reported offences (Barnham et al. 2017).

The issue of frequency and decreasing intermittency over time has been established across the literature. In inter-personal violence, for those couples engaged in repeat domestic abuse, a strong pattern of escalating frequency was found in Australia (Kerr et al. 2017). In the UK, some evidence was found of escalating frequency for 'chronic' repeat domestic abuse victims (Bland and Ariel 2015). Conversely, in Canada, an initial increased risk of burglary was identified with half of secondary burglary victimisations happening within a week, before the risk started decreasing (Polvi et al. 1991). This 'decay curve' evidencing reducing risk over time has been established across studies in burglary re-victimisation (Pease et al. 2018). Increased risk of repeat victimisation is also affected by being in a high-crime area where the probability of suffering a repeat increases (Trickett et al. 1992; Kleemans 2001). This spatial-temporal overlap for repeat victimisation has been identified across jurisdictions and has enabled police forces to target concentrations (Johnson 2008).

Beyond these concepts, repeat victimisation continues to be found consistently across offence types as well as all-crime collectively (Farrell 1995). A recent study in Dorset identified that repeat victimisations accounted for 12.14% of crime, with victims experiencing a range between 1 and 14 crimes a year (Dudfield et al. 2017). A further study showing similar proportions of repeat victimisation in Avon and Somerset also identified four victim-outliers reporting 276, 210, 111 and 97 offences respectively over two years (Dudfield et al. 2017; White 2018).

2.3. What explains repeat victimisation?

Repeat victimisation can be explained using the aforementioned lifestyle theory, with characteristics of repeat victims giving insight into how victims can be 'agents' of their own victimisation (Davis, Taylor and Titus 1997 cited in Pease 2008). A meta-analysis of 66 studies that tested the empirical link between self-control and victimisation found that self-control is a consistent predictor of repeat victimisation, with further research showing self-control to be significant because it mitigates risky lifestyles (Pratt et al. 2014; Turanovic and Pratt 2014).

Building upon rational choice theory above, the `structural-choice model' incorporates contextualisation, for example, it includes the victim's proximity to a crime hotspot (Miethe and Meier 1994). Miethe and Meier (1994) argued that victim exposure, proximity to crime, 'target attractiveness' and the presence of a guardian are important correlates of victimisation. Given these components, it becomes clear why victimisation is relatively rare, with the majority of the population being *immune.* Those that are victimised are often not repeat victims, however there are a small number of *chronic* victims (Hope and Trickett 2008; Bottoms and Costello 2010a; Farrell 1995). This leads to the point that the best predictor for victimisation has been shown to be prior victimisation, with repeat victimisation often occurring promptly thereafter (Pease 1998; Bottoms and Costello 2010a).

Two additional pairs of overlapping concepts relate to ‘flag’ and ‘boost’ models and ‘risk heterogeneity’ and ‘event dependence’ respectively. Risk heterogeneity refers to ‘chronic’ victims who have stable characteristics that predicate an ongoing risk of victimisation, whereas event dependence refers to ‘fast repeats’ that occur swiftly as a result of the initial victimisation before ceasing, for example due to temporary exposure or poor security (Hope and Trickett 2008; Pease 2008; Pease and Farrell 2016; Pease et al. 2018; Bottoms and Costello 2010a).

2.4. Focusing on Harm

Harm can be defined as ‘the impairment of an interest deemed worthy of legal protection’ (Paoli and Greenfield 2013, p.360). The reason for a shift towards harm over a count of crime is because ‘crimes are not created equal’ and to compare victimisations so imprecisely provides a weak measure of the effect of police outputs (Sherman 2013). Beyond repeat victimisation, the bulk of crime is actually concentrated on a limited number of victims (Ellingworth et al. 1995).

Focussing on concentrations at a micro-level was first identified in relation to *places*, where 3.3% of street addresses in Minneapolis were identified as being responsible for 50.4% of all calls (Sherman et al. 1989). Sherman et al. (1989) also discovered even greater concentrations among certain offence types. These small proportions of a unit, namely victims, offenders or places, that are responsible for the greatest accumulative harm, have been labelled the ‘Power Few’ (PF) and follow the ‘Pareto Curve’ pattern of distribution (Sherman 2007).

There is a plethora of evidence on harm concentrations, with different types of units of analysis. For example, concentrations have been found in familial settings with approximately 20% of families experiencing nearly all serious violence, and 1.7% of all couples being accountable for 80% of all domestic abuse related harm over a six-year period (Rima et al. 2019; Bland and Ariel 2015). In relation to individual victims, a study in Kansas City identified that 3% of the city's population and commuter population suffered 20% of all crimes over a five-year period (Sherman et al. 1991 cited in Sherman 1992). In Dorset, 85% of crime harm was suffered by under 4% of all victims (Dudfield et al. 2017). To put this into perspective, Dudfield et al. (2017) found that those in the PF suffered 15 times more harm compared to the average harm suffered by the Non-Power Few (NPF). One domestic abuse study across multiple forces found 80% of crime harm was attributable to 2.7% of victims (Bland 2020a). Furthermore, victim concentrations are present in social networks, for example one study showed that networks accounting for just 6% of the city's population, were attributable to 70% of the victimisations (Papachristos et al. 2015). Understanding these patterns and concentrations of victimisations is a necessary precursor to predicting crime (Sherman 2019).

2.5. Under the Bonnet of Harm Measurement

Harm can be measured in different ways, and there are different techniques for estimating the severity of victimisation. Early attempts to assess severity started with a Crime Seriousness Index which used surveys as a vehicle to weight crimes (Sellin and Wolfgang 1964 cited in Ratcliffe 2015). Similar attempts utilising bigger sample sizes to increase validity, combined interviews and surveys to determine crime seriousness based on public opinion found consensus among the population on ranking crimes by severity, albeit with some variance between subgroups (Rossi et al. 1974; Wolfgang et al. 1985). Challenges with quantifying harm, however, include factoring-in the level of causality, simplicity and translation to policing (Paoli and Greenfield 2013; Ratcliffe 2015; Greenfield and Paoli 2013).

The Cambridge Crime Harm Index (CCHI) was developed as a straightforward and affordable 'barometer' to measure harm using the starting point within sentencing guidelines to weight crimes by the number of days imprisonment for each offence; using the starting point thereby avoids outliers distorting the measure (Sherman et al. 2016; Sentencing Council n.d.). This approach reflects the harm *actually* done rather than considering mitigation or offender antecedents which may skew a true representation of harm (Sherman et al. 2016). The index was designed to meet a three-part test that included the 'democracy test', whereby any method should reflect public opinion; the 'reliability test', whereby the method provides consistent results; and the 'costs test', whereby the method has minimal cost implications to operationalise (Sherman et al. 2016). The CCHI methodology can be followed by police forces to multiply every crime a victim suffers by the weighting system to rank order concentrations of harm to then effectively target resources (Sherman et al. 2016).

A second harm index, the Office for National Statistics (ONS) Crime Severity Score (CSS), weights crimes by the length of the mean custodial sentences given (ONS 2016). A detailed comparison of the CCHI and CSS identified weaknesses in both approaches, for example the CSS would take account for sentencing reductions through early guilty pleas which are unrelated to harm suffered by the victim (Ashby 2018). Ashby (2018) concludes without recommending one approach over another, simply that one should be chosen and used unanimously. Both indexes stood out in a comparison of several major models using the three-part test advocated in Sherman et al. 2016 (Bland 2020a). In this assessment the CCHI prevailed on the basis of reliability given its stability over time and the CSS's imbalance in some offence categories based on victim gender (Bland 2020a). Harm and crime count collectively provide a greater understanding of crime, with the ability to measure severity and frequency, for example a victim may suffer such a serious crime that they are categorised as high-harm victims when in truth they may not be harmed again.

2.6. Forecasting Harm

Prediction builds upon explanation and can be defined as the extent to which a 'criterion measure', such as victimisation, can be predicted by measuring one or more preceding variables such as prior victimisations or age (Farrington and Tarling 1985). This subchapter reviews the dichotomy between two methods of prediction; professional or clinical judgement on the one hand and statistical, actuarial forecasting on the other.

Conventional police tradecraft can involve officers relying on professional intuition and gut-instinct rather than the evidence-base (Sherman 2015). Clinical prediction can be useful, especially in dynamic situations, however, over-trusting it can be limiting (Kahneman 2011). One study showed that 97% of officer-perceived hotspots were actually not, with the majority of actual hotspots not identified by officers; highlighting that professional judgement can be inaccurate and that statistical forecasting should be utilised to inform preventative policing (Macbeth and Ariel 2019). A further experiment to test judgements of high-crime places and offenders established that officers were respectively 95% and 74% inaccurate (Sutherland and Mueller-Johnson 2019).

On the other hand, prediction can be based on statistical forecasting. A primary method is to utilise algorithms, for example using 'random forests' with predictors to calculate risk. This in turn, has also attracted criticism, for example due to limited transparency, privacy breaches, their complexity, and potential for unfair, unjust or inaccurate decisions being determined by the program, especially when the algorithm is built using bias data (Oswald et al. 2018; Bland 2020b). Bland (2020b) did highlight that specific forecasting techniques do have advantages, for example 'random forests' modelling, allows thresholds to be built into trade-off error rates.

Statistical forecasting based on previous crimes varies dependent on the unit of analysis. For places, prediction is possible due to the strong and stable 'coupling' of crime to place over time, as shown in Minneapolis (Weisburd et al. 2012; Sherman et al. 1989). Conversely, for offenders, data from Thames Valley Police showed that from a PF cohort of 610 offenders in year one, 21 remained in year two, 1 in year three and none in year four (Liggins 2017). This mirrors a domestic abuse study that established that highest-harm offenders could not be easily identified prospectively (Barnham et al. 2017).

Demonstrating the conditional probability of victims remaining in the PF cohort was explored in Avon and Somerset, demonstrating that over two years, 634 victims remained in the PF, which represented 8.3% and 8.5% of each year's PF respectively (White 2018). One limitation is that this study did not use a lengthy time-course, however it still demonstrates that if the entire PF cohort had been focussed on, there would be over 90% false positives amounting to resource implications.

Prediction based on variables has also been explored, for example one study found that 40% of offenders involved in intimate-partner homicides were known to have suicidal indicators (Bridger et al. 2017). Further studies have shown that different risk factors such as drug-use and sexual assertiveness can predict sexual victimisation (Testa et al. 2007). The use of algorithms has also been used to predict victimisation by certain crime types, for example Hu et al. (2020) identified certain characteristics, such as age and lifestyle traits; including online shopping frequency, were predictors of identity theft.

2.7. Targeting Repeat Victimisation

Targeting repeats can be effective, for example, by reducing burglaries by up to 80% without displacement of crimes to other areas (Forrester et al. 1988). A systematic review of 31 studies across crime types showed that targeting repeat victimisation *can* lead to crime reductions, especially when tailored and contextualised (Grove et al. 2012). Justification for this approach is clear when considering that the conditional probability of additional victimisations increases with each consecutive victimisation (Ellingworth et al. 1995; Bottoms and Costello 2010a; Bland and Ariel 2015; White 2018). This evidence was based on analysis establishing the likelihood of a further victimisation based on the prior number of victimisations. Targeting smaller concentrations of high-harm victims utilising this evidence could potentially reduce harm.

Repeatedly harmed victims and 'victim careers' may be defined by 'within-crime type' or 'across-crime type' victimisations meaning targeting strategies must be bespoke (Farrell et al. 2001).

Research using victimisation surveys has found that 28% of victims suffered one of the nine crime types reported on, 14% suffered two and 10% suffered three or more crime types evidencing the plurality of victimisation (Johnson 2005). This research found that 19% of victims suffered two offences within-crime types, and 13% suffered three or more crimes in the one crime type with the most likely being assaults/threats. Further research has developed this into predictive modelling, for example violent victimisation in individuals' youth is significantly linked to the risk of violent victimisation in adulthood (Tillyer 2013).

2.8. Victim-Offender Overlap

The VOO describes individuals who are both a victim *and* an offender within a short period of time (Bottoms and Costello 2010b). A systematic review of 37 studies identifying that 31 evidenced the overlap across different cultures, populations, crime types and settings; with the other six having mixed results (Jennings et al. 2012). In Leicestershire, in a cohort of all victims and offenders, 3.2% were victim-offenders that were responsible for 74.5% higher harm compared to the average within the cohort, with it being more likely to become a victim after offending than vice versa, at 17.9% and 2.6% respectively (Sandall et al. 2018). A subsequent study into 10,000 knife-crimes in Thames Valley Police showed that 610 victim-offenders committed 7.2% and experienced 6.7% of the crime (Bailey et al. 2020).

This overlap has been evidenced between sexual victimisation and offending (Jennings and Meade 2017), and intimate-partner violence with between a quarter and a third of samples being victim-offenders (Muftic et al. 2012; Tillyer and Wright 2014). For serious assaults, 68% of victims reported serious assault offending, with victimisation being the main predictor for offending (Singer 1981). One study into violence found that many people had a clear and consistent predominance over time to mainly being a victim or offender (Schreck et al. 2008). A recent study into violence indicated that 6% of the victim population were victim-offenders, with those being predominantly offenders suffering 2.7 times as much harm as unique offenders, and those being predominantly victims suffering three times the harm of unique victims (Hiltz et al. 2020).

Von Hentig (1940; 1948) first identified that a victim's behaviour is relevant to offending, for example by being 'greedy for gain', and explained that some victims may not report crime because they may not want to expose their own criminality to the police. Wolfgang (1958) identified the overlap and that would-be offenders can become victims, highlighting 'victim-precipitated' murders as an example and identifying that these victims generally had more criminal antecedents compared to other victims.

Two theories have emerged to explain VOO; namely dynamic causal perspective and population heterogeneity perspective, which are also referred to as state dependence and risk heterogeneity (Jennings et al. 2012; Ousey et al. 2010; Lauritsen and Laub 2007 cited in Bottoms and Costello 2010b). Dynamic causal perspective encapsulates the causal relationship where victimisation or offending leads to the other, for example someone seeking revenge after being victimised (Ousey et al. 2010). One study found that victimisation, along with other factors, informed decision-making that consequently predicted violent offending (Averdijk et al. 2016).

Dynamic causal perspective includes rational choice theory, lifestyle and cultural theories, with research showing that victim-offenders are unique and differ in their activities to victims (Ousey et al. 2010; Klevens et al. 2002). Lifestyle traits can predict both victimisation and offending, for example offending, proximity to offenders, and drug and alcohol use can result in an increased risk of victimisation (Gottfredson 1981; Lauritsen and Laub 2007; Muftic et al. 2012). General strain theory also fits here, whereby external strains, including victimisation, lead to law-breaking such as retaliation (Agnew et al. 2002; Agnew 2002 cited in Schreck and Stewart 2012).

Population heterogeneity perspective centres on victims and offenders sharing stable characteristics that are predictors of crime, an example being risk-seeking (Lauritsen and Laub 2007; Ousey et al. 2010). Gottfredson and Hirschi's (1990) General Theory of Crime identifies the relevance of Control

Theory, where people's natural desire for pleasure and gain, is restrained by legal and social constraints using the mechanism of self-control. Low self-control and 'risk-seeking' can be a predictor for victimisation and offending; with these individuals being impulsive, needing immediate enjoyment that's easy to achieve, lacking emotional awareness and ignoring long-term consequences; meaning they *may* indulge in criminal activities (Baron et al. 2007; Gottfredson and Hirschi 1990). One recent study found that 39.8% of victims had a criminal record and victims, offenders and victim-offenders tended to share characteristics around age, gender and ethnicity (Bailey 2019). This mirrors a finding by Broidy et al. (2006) that victimisation and offending are highest among certain demographics based on age, ethnicity and residence.

2.9. Summary

Victimisation is the best single predictor of future victimisation, meaning analysis of this variable to predict crime is well-grounded (Pease 1998). Similarly, the emphasis on identifying suitable targets based on evidence to enable contextualised interventions has been established. The core theories of victimisation have been reviewed to explain why some individuals may be more prone to crime. Linked to this is the identification of how demographics are correlated to a greater risk of harm, which is supportive of further analysis (Gale and Coupe 2005).

In certain crime types, escalation has been shown to be rare and the increasing frequency of repeat victimisations has been centred on chronic victims, both of which, would benefit from an exploration across an entire victim population. Similarly, some victims are prone to victimisation across crime types, whilst others suffer only one type of crime; something pertinent when considering intervention strategies. Different victim classifications may also emerge, for example in PF offenders, 'one-timers' and 'chronics' were identified; requiring differential police responses (Liggins 2017). 'One-timers' limit prediction, with one study identifying that there was no prior arrest in the two years preceding serious domestic abuse in 51% of cases (Bland 2020a). Typologies are not new;

Bland and Ariel (2020) conducted analysis based on single, repeat and serial domestic abuse offenders as well as sub-categorisation with ‘family only’, ‘violence offences only’ and ‘generalists’.

Research exploring the concentrations of crime across certain high-harm crime types, as well as subtleties of across-crime type victimisation is needed as they have been largely unexplored (Farrell et al. 1995). Similarly, the conditional probability of suffering further offences across all crime, rather than by specific crime types is desirable. The value of complementing crime count with a measure of harm has been established and a comparison of harm indexes has identified the CCHI as the forerunner.

Statistical forecasting offers a logical alternative to current practice that can be easily replicated. Linked to forecasting and the power few, is the need to establish what unit of time and what concentration of high-harm victims provides the greatest predictive accuracy. Finally, the higher levels of harm attributable to victim-offenders and theoretical perspectives explaining the overlap have been reviewed. Analysis of the VOO across all crime, as well as establishing when in the life-course the overlap occurs, as identified by Jennings et al. (2012), is needed to support targeting.

These areas are identified with the intention of optimising the accuracy of prediction to support harm reduction. Based on these identified gaps, research questions have been developed with the next chapter setting out the methods applied to answer these questions.

3. METHODOLOGY

3.1. Introduction

This chapter details the research design, including the data used, their importance, and how data were retrieved. Details are provided on both the development of the datasets, how harm scores were computed, and data cleaning. The analytical techniques used are then discussed, with the inclusion of relevant parameters and definitions adopted to support replication of this study. The final sections give commentary on ethical deliberations and consideration around external validity.

3.2. Research Design

3.2.1. Design

This study incorporates a descriptive analysis of distributions, patterns and concentrations of crime incidence, harm, and police victimisation data. Survival analysis is conducted to establish the accuracy of forecasting concentrations of harm among the Power Few. Offender data has been utilised to research the victim-offender overlap.

3.2.2. Data Source

The data consist of police crime records retained by Kent Police on its Record Management System called Athena. All police forces record crimes in line with the National Crime Recording Standard (NCRS) and Home Office Counting Rules for Recorded Crime (HOCR) (Home Office 2020b). The aim of these guidelines is to ensure consistent and accurate crime-recording that inspires victim confidence (Home Office 2020b). In 2017, Kent Police was graded as 'Inadequate' in an HMICFRS Crime Data Integrity inspection designed to scrutinise crime-recording performance; establishing a compliance rate of 83.6% meaning approximately 24,300 crimes a year were not converted into crimes from incidents (HMICFRS 2017). After substantial intervention, a 2018 reinspection graded

Kent Police as 'Outstanding' in Crime Data Integrity, with a 96.6% compliance rate, suggesting the force now uses a reliable measure of crime-recording for *reported* crime (HMICFRS 2019b). Ongoing quality assurance mechanisms ensure robust oversight of this standard.

Athena was implemented in September 2017 with extensive Back-Record Converting; meaning all crime data held on the previous system called Genesis, were transferred across to the new system. Each victimisation is held as a 'Crime Investigation' recorded under an 'Event' category and has links to 'People', 'Objects' and 'Locations', which allows further variables to be extracted.

3.2.3. Data Architecture

The data were extracted by Kent Police analysts utilising SAP Business Objects to draw information down from Athena and convert the information into datasets in Excel. Six calendar years' worth of total crimes committed between 1st January 2014 and 31st December 2019 are detailed in Table 1. A six-year period was chosen to overcome seasonal fluctuations of crime (Hatry and Newcomer 2015).

Table 1. Total Crime Counts Recorded by Kent Police; 2014-2019

	2014	2015	2016	2017	2018	2019
January	9930	10241	11164	13216	16517	16373
February	8171	8263	8984	10587	13229	14020
March	9436	9280	9722	12008	15529	16140
April	9230	9051	9669	12426	16012	15539
May	9657	9347	10687	14138	18135	15707
June	9701	9256	10750	15754	17315	15717
July	9721	9687	11036	16245	18177	16854
August	9403	9507	11262	14906	16657	15899
September	9044	8873	10812	14550	15978	15334
October	9161	9970	11002	14608	16203	15806
November	8852	9512	10733	14408	15669	14918
December	8843	10003	11628	13865	15239	14390
Total	111149	112990	127449	166711	194660	186697
					Grand Total	899656

Parameters were introduced to ensure consistency with the victim-based harm focus of this research; only crimes with a unique named victim were included, therefore excluding business crime and those crimes against society where there was not a named victim, such as possession of offensive weapons. This research seeks to support operational targeting; therefore, the measure of crime includes only those offences committed *within* these time parameters, thus excluding historic offences *reported* during this period. With these parameters in place, a total of 677,462 reported crimes were identified; each with a Unique Reference Number (URN). The variables identified in Table 2 were extracted as they support an assessment by crime type; tiered by offence-specification, socio-demographics and time periods. The victim variables allow analysis by unique victims, socio-demographic variables and 'flags'. 'Flags' for the purpose of this research refer to keywords that denote characteristics of the offence, victim of offender such as 'Domestic Abuse', with additional keywords such as 'emotional abuse' or 'financial abuse'.

Table 2. Variables Extracted for Datasets

Crime Variables	Victim/Offender Variables
Crime URN	Victim URN
Crime 'Flags'	Victim Gender
Offence name	Victim Age (at time of offence)
HMIC Crime Tree Level 2	Victim Date of Birth
HMIC Crime Tree Level 3	Nationality
Home Office Offence Code	Country of Birth
Home Office Offence Sub-Code	Ethnicity
Home Office Offence Sub-Sub-Code	Victim's Address - Town
Home Office Classification	Victim's Address - LSOA
Committed Date	Victim 'Flags'
Reported Date	
Location of Offence - LSOA	
Location of Offence - Town	
Location of Offence - Ward	
Outcome	

The same variables were extracted for the offender dataset for those offences *committed* in the time period, however no offences were excluded. This dataset is separate from the victim dataset and was only used for the purposes of examining a victim-offender overlap. A total of 116,066 records were retrieved across the six-year period. Offenders were determined by those suspects who received a positive outcome. Appendix A provides details of all recorded outcomes and are categorised as those considered to be 'detected' with a positive outcome.

3.2.4. Data Protection

The research itself was approved by Chief Officers and following advice from the force's Data Protection Manager, the datasets were anonymised, for example using URNs rather than names.

3.3. Data Development

3.3.1. Crime Harm Scores

In order to answer the research questions and understand concentrations of harm, a Cambridge Crime Harm Index (CCHI) value was added to every unique crime. The victim and offender datasets are both held in Microsoft Excel, the same program used for the CCHI. A common variable in both datasets and the 'Cambridge Crime Harm Index 2020' are the Home Office Classifications (Cambridge Centre for Evidence-Based Policing 2020). Using a 'VLOOKUP' function against these codes, the corresponding CCHI value was calculated to weight each crime with a harm score. This method of translating crime into numerical values produces a ratio level measurement that also enables counting and rank ordering (Ruane 2016).

The methodology of the CCHI is to weight each crime by the number of days imprisonment an offender would be recommended to receive using the starting point under Sentencing Guidelines (Sherman et al. 2016). This makes the presumption that the basic offence has been committed by a first-time offender without weighting mitigating or aggravating factors. This provides a metric that is consistent in 'calibrating' harm when applied to police crime data (Sherman et al. 2016). This methodology converts all sentences to a total number of days, regardless of whether the sentence would amount to imprisonment, community service or fines (Sherman et al. 2016). An example of these harm scores, set against Home Office Classifications can be found in Appendix B. It is acknowledged that there are limitations with this index, for example, it calculates harm based on offence type rather than the specific case where, in reality, the level of harm would vary (Ashby 2018).

Sentencing Guidelines for England and Wales are the responsibility of the Sentencing Council. Guidelines are established based on a rigorous process that produces different sentencing tiers based on the harm suffered and culpability of the offender (Sentencing Council 2020). Guidelines exist for a substantial number of offences, however where no guidelines exist, the court refers to the Council's 'Overarching Principles' and Court of Appeal judgements for similar cases (Sentencing Council 2020).

3.3.2. Data Cleaning

An initial 'pre-mortem' analysis to foresee plausible issues that may impede the research identified blank cells, duplicates and inconsistency with the application of the 'flags' (Klein 2007). To overcome this, data cleaning was undertaken to systematically remove duplicates and address incomplete or missing fields as these are known to create barriers for analysis (Farrell 1995). Considerations were made as follows; murders *were* included within the dataset; despite the obvious implication for operational targeting, the data were relevant in analysing escalation and could be filtered out if operationalised. Furthermore, 'flags' appeared to be inconsistently applied, for example, domestic abuse can include financial, emotional and physical abuse; however, of 34,626 domestic abuse offences categorised as violence *with injury*, only 2,700 reports had a 'physical abuse' flag, amounting to 7.8%. The question of validity in these 'flags' being accurately applied, and low usage resulted in these being excluded from this research. The issue of data quality when using data as an indicator of future harm to support targeting is acknowledged as a limitation (Maltz 2010; Farrington and Tarling 1985).

A final consideration related to missing CCHI scores; there were some rare crime types that were not covered by the latest version of the CCHI. These records totalled 101 victimisations amounting to 0.015% of the victim dataset, which were subsequently removed. There were no such anomalies in the offender dataset. Table 3 below shows the final number of crimes and unique victims in each of the datasets after data cleaning.

Table 3. Dataset Totals After Data Cleaning

Victim Dataset	Count
Number of Victim-Based Crimes	677,361
Number of Unique Victims	380,169
Offender Dataset	Count
Number of Crimes with an Offender	116,066
Number of Unique Offenders	52,448

3.4. Data Analysis

This section covers the procedures employed to establish how accurately high-harm victims can be predicted based on the history of prior victimisation.

This research is primarily victim-focussed and so the principle data point utilised is a victim's URN. For the purpose of this analysis, a victim is a named individual who has suffered a recordable crime. An offender has been identified based on a positive outcome being recorded against the individual as outlined above. Repeat victims and offenders are assessed as those who have suffered/committed two or more offences in the period of time under analysis. Crime count is analysed in addition to harm to separate repeat victims from single-offence victims. Additionally, a victim could be at risk of suffering further victimisation despite suffering low harm, for example, as part of stalking against a domestic abuse victim.

3.4.1. Power Few

Annual Patterns of Concentrations

In order to establish the Power Few for each year, using their URNs, every victim had the harm score for each crime they suffered summed to give their total harm score. Within the dataset, victims were then ranked in descending order with the highest harmed victim through to the lowest harmed victim. The highest-harmed victim's score was then calculated as a percentage of the total harm suffered by the whole victim population. For each sequential victim, their harm score was summed with each victim above them, thus giving cumulative harm scores and proportions of total crime harm as demonstrated in Table 4 below. This cumulative percentage allows a description of the distribution amongst the victim population including concentrations based on percentages of harm, for example at 80%; a replication of Dudfield (2016).

Table 4. Rank Ordered and Cumulative Harm Scores

No. of victims*	Victim URN	Sum of Victim CCHI	Cumulative Sum of Harm	% of total harm**
1	8783701	67160	67160	0.09%
2	8781147	46194.5	113354.5	0.15%
3	8600517	41361.5	154716	0.21%
4	9375745	41268	195984	0.26%
5	10422455	39439	235423	0.32%
6	9104119	37434.5	272857.5	0.37%
7	8852867	36555	309412.5	0.42%
8	8653056	36106.5	345519	0.46%
9	9392962	33442.5	378961.5	0.51%
10	8826400	32614	411575.5	0.55%

*Total number of unique victims equals 380,169.

**Sum of total harm for all victims equals 74,320,040.

When setting thresholds, such as the number of people that suffered 80% harm, two methods were applied. The first method (Method 1) chose the first victim in the rank ordered list to reach the respective threshold and then that victim and all those with a higher harm score were identified as the Power Few (PF); a proportion of all victims that suffered the corresponding percentage of total harm. This method is objective and allows for concentrations to be easily identified and simply stated. The issue with this method is that a proportion of victims shared the same harm score at certain thresholds, which fluctuated over time. By way of example, when replicating Dudfield et al.'s (2017) research, in 2019 at the 80% harm threshold, the individual victim harm score was 365; 7080 victims shared this harm score. If these victims were excluded from the Power Few, 7525 victims would remain; if included, the Power Few would consist of 14,605 victims. The second method (Method 2) therefore applied clinically meaningful cut-offs at a point closest to the threshold where the harm score changed, in order to support operational targeting. Victims were then coded with a '1' for PF and '0' for Non-Power Few (NPF) to support subsequent analysis.

CCHI Totals, Harm Ratios and Consistency in the Shape of the Distribution

From the aforementioned tables, a descriptive analysis of the total CCHI scores for these concentrations could be completed and mean harm scores of the PF and NPF used to determine a comparative harm ratio. Using different units of time, for example years or months, as well as sequential time periods, the consistency in the shape of the distribution was analysed by comparing the proportion of victims in the PF, their cumulative harm scores and the PF/NPF harm ratio.

The same process was repeated for count data and further repeated for different periods of time, for example years or months, as well as for certain offence types. Some single offence types such as rape were only analysed using count as the harm scores were equal. Unless otherwise stated, the PF victim cohorts were determined as shown in Table 5 below and will be described in this research as shown.

Table 5. Power Few cohorts

	Harm		Count	
	Descriptive	Naming Convention	Descriptive	Naming Convention
Power Few Victim Cohort - Threshold 1	Highest-Harmed Victims Cumulatively Suffering 10% Total Harm	PF (10% Harm)	Highest-Incidence Victims Cumulatively Suffering 10% Total Count	PF (10% Count)
Power Few Victim Cohort - Threshold 2	Highest-Harmed Victims Cumulatively Suffering 80% Total Harm	PF (80% Harm)	Repeat Victims (Suffering 2+ Victimisations)	PF (Repeats)

3.4.2. Power Few – Versatility

Versatility refers to multiple crime types. Using the HMIC Crime Tree Level 2 variable, as detailed in Appendix C, a pivot table was created to count the number of crimes each PF victim suffered under each of the categories. The PF were taken as those responsible for 80% of all crime harm over the full six-year dataset. Utilising 'IF' formulas, each victim was identified as a repeat victim or 'one-timer' and whether they had suffered crimes under just one crime category (specialists) or multiple categories (generalists). This enabled proportions of each category to be assessed and was replicated for count using repeat victims as the PF.

3.4.3. Survival Analysis

Survival analysis here refers to the presence of the victims in the PF for one period of time, remaining in the PF in subsequent periods of time.

Survival Across Six Years by Unit of Time

Based on Method 2 above, concentrations using the 80% harm threshold were determined for different periods of time, namely, every year, bi-annual, quarter and monthly. In order to do this, a series of calculations were made; firstly, the 80% total harm cut-off was determined, then the respective victim's harm score at that point was established, then how many victims shared that harm score, and then how many victims had a higher and lower harm score. The PF for the first time period, for example 2014, then *excluded* all those that shared the same harm score at that percentile point to give a smaller PF cohort with a marginally reduced collective harm score as a result. For each consecutive period of time, the PF cohort *included* those that shared the harm score at the 80% point in order to not arbitrarily exclude PF victims. A 'COUNTIFS' formula was then used to establish the survival of victims in each consecutive PF over time across the six years, demonstrating consistency. This enabled a comparative description of the units of time to determine which produced the greatest consistency for prediction.

This methodology was repeated for a 10% harm threshold, the top 100 victims in the PF and repeated for both harm and count. For survival analysis against count, only repeat victimisations were used because the 10% threshold predominantly sat at two victimisations; the same as the repeat victim threshold. The issue identified otherwise, is that single victimisations would need to be included, undermining the purpose of targeting predictable concentrations. This is also in line with previous repeat victimisation studies.

Crime Types

In order to gauge potential crime types for targeting, Method 1 was adopted as a more clinical approach. A 'COUNTIFS' formula was used to establish the survival rate over consecutive years.

Survival of the 2014 Power Few

The PF (harm and count) for each initial time period were then analysed using Method 1 to determine how many remained in the PF in each time period irrespective of their status in intervening years, for example, the PF from 2014 were analysed for their presence in the PF in 2019, whether or not they were in the PF in the years between.

Survival – Period to Period by Units of Time

In addition to survival over the 6 years; for both harm and count at the respective thresholds, survival analysis was conducted from one period of time to the next for bi-annuals, quarters and months. This was done using the latest periods of time in the dataset and working backward to incorporate recency, as demonstrated by Table 6 below. This enabled a further four replications of the analysis due to the longitudinal nature of the dataset to find mean survival rates and provide greater validity to the results.

Table 6. Survival Analysis; Period 1 to Period 2

Unit of Time	Period of Analysis				
	Analysis 1	Analysis 2	Analysis 3	Analysis 4	Analysis 5
Annual	2018-2019	2017-2018	2016-2017	2015-2016	2014-2015
Bi-Annual	B1 2019 - B2 2019	B2 2018 - B1 2019	B1 2018 - B2 2018	B2 2017 - B1 2018	B1 2017 - B2 2017
Quarter	Q3 2019 - Q4 2019	Q2 2019 - Q3 2019	Q1 2019 - Q2 2019	Q4 2018 - Q1 2019	Q3 2018 - Q4 2018
Month	M11 2019 - M12 2019	M10 2019 - M11 2019	M9 2019 - M10 2019	M8 2019 - M9 2019	M7 2019 - M8 2019

Survival – PF Remaining Victims Regardless of Staying in the PF

Further analysis using Method 1 established for both harm and count, how many victims from the PF in 2014 remained *victims* in subsequent years, whether or not they were in the PF. Using the rank ordered data, Excel functions were used in the same way as above to establish the proportion of PF victims that remained victims year-on-year. Comparative analysis was conducted on survival rates of PF victims remaining in the PF, PF victims remaining victims regardless of remaining in the PF, and all victims remaining victims in subsequent periods of time. Specificity and sensitivity analyses were conducted against these three groups; summing false positives, false negatives, true positives and true negatives as demonstrated in Table 7, and then calculating the Positive and Negative Predictive Values (Cochrane UK n.d.). This enabled a comparison of the three groups to determine which was most accurate in terms of prediction.

Table 7. Specificity/Sensitivity Analysis

	Re-Victimised	Not Re-Victimised
PF Victim Predicted to be Re-Victimised	True Positive	False Positive
NPF Victim Predicted to not be Re-Victimised	False Negative	True Negative

*Positive Predictive Value = True Positives / (True Positives + False Positives)
**Negative Predictive Value = True Negatives / (True Negatives + False Negatives)

3.4.4. Escalation Across the Victim Population

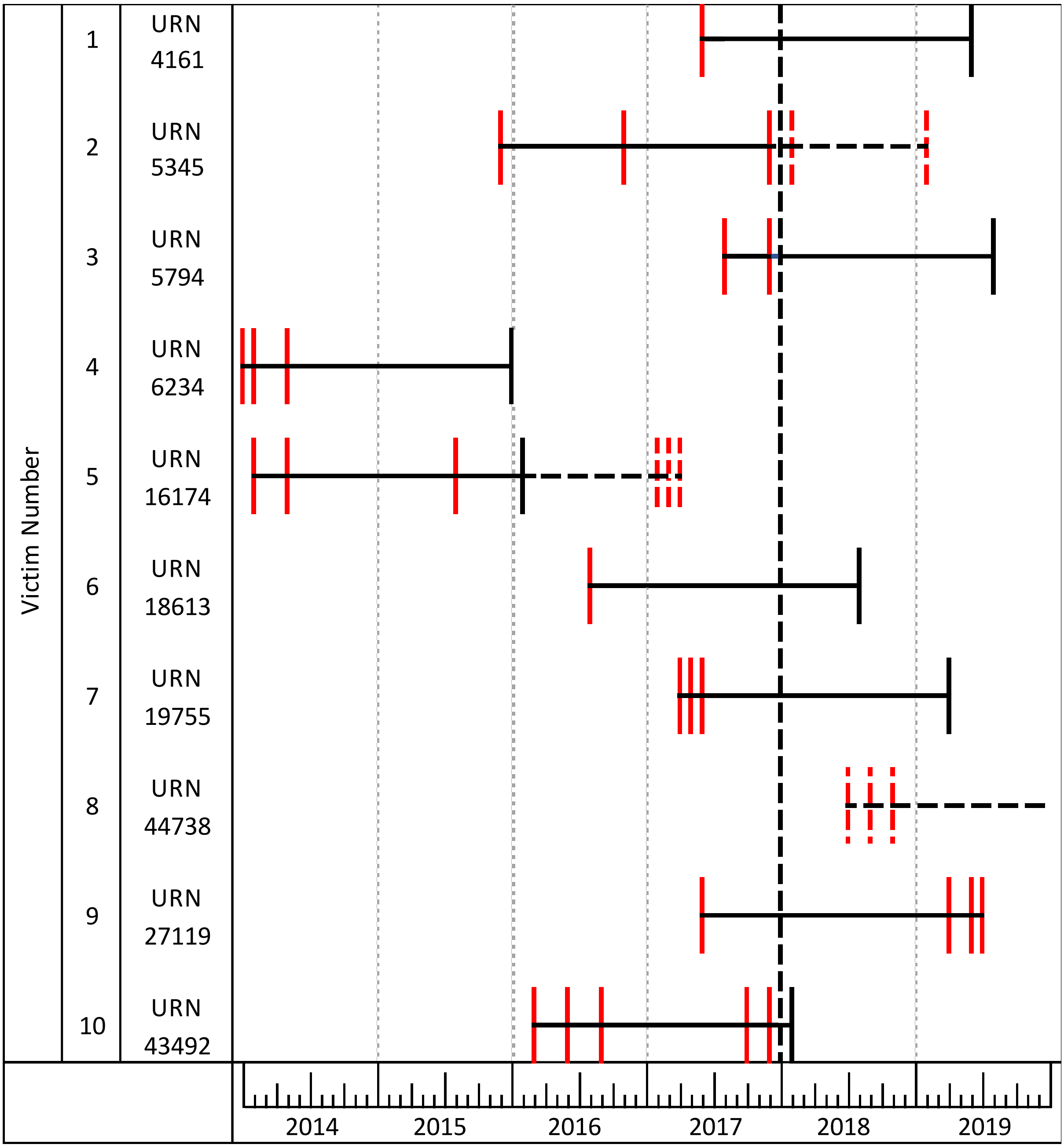
Out of the full six-year PF cohort that suffered 80% harm, the repeat victimisations were analysed to establish whether there was an escalation in the harm they suffered with each sequential crime. Escalation here was measured as an offence having a higher harm score than the prior offence; de-escalation and 'no change' could also occur. Using the 'repeat number' and harm score variables against the URNs, an 'IF' formula was utilised to code the direction of travel, signified with 'escalation', 'de-escalation' and 'no change' values. This identified the number of repeat offences that fell into each of these categories.

Further 'IF' formulas were then used alongside the Victim URN to establish the proportion of victims that suffered a series of repeat escalations without a break. In addition to this 'pure' escalation, analysis was repeated to incorporate escalation with intermittent 'no change' in harm scores where escalation continued thereafter without de-escalation.

3.4.5. Conditional Probability

Conditional Probability (P(A|B)) here refers to the probability that a victim will suffer a further crime given the first. This univariate analysis was conducted against the entire victim dataset with two parameters put in place.

To maintain validity, the data was left and right censored to ensure an even follow-up period for each victim. Without this, patterns would be skewed as those at the start of the time period would have longer to suffer a further victimisation than those that were first victimised later. The dataset covers the period inclusive of 2014 to 2019; left censoring was therefore applied to calibrate the starting point of each victim using their first victimisation and then calculating and including sequential victimisations within the two-year follow-up period; namely 730 days. Right censoring was applied at the end of 2017 to enable the 2-year follow-up period. Figure 1 below demonstrates this censoring against ten victims within the dataset. Victims 1 and 6 are single-offence victims. Victims 2 and 5 suffered three victimisations within the 2 years, with further victimisations after the left censoring was applied; meaning those were disregarded. Victims 3, 4, 7, 9 and 10 suffered multiple victimisations during the censored period, and victim 8 suffered offences after the start of 2018 when right-hand censoring was applied; as a 2-year follow-up was not possible, this individual's victimisations were excluded from the analysis.



*Victimisations indicated in red.

Figure 1. Example of Ten Cases with Left and Right Censoring of Victimisations

A secondary issue related to same-day offences. The data provided individual dates but not times and without these, or a qualitative review of each victimisation, it was not possible to determine whether same-day offences were part of the same incident. The number of same-day offences totalled 29,505 victimisations within the six-year period out of a total of 677,361, which equates to 4.36%. Out of the 380,169 unique victims in the dataset, 20,132 (5.3%) suffered same-day offences.

This issue does not detract from the fact that the harm was suffered, however, for this section of the analysis and the section below (frequency), these same-day offences were removed as they could skew the data. The repeat number for each victim was then calculated in addition to the sequential victimisation day to understand how many repeats each individual had suffered over time.

3.4.6. Frequency of Repeat Victimisation

Using the above censored data, the victim URNs, repeat number and sequential repeat victimisation day variables, a count of the number of victims against each repeat number over time was calculated. Time was calculated by consecutive numbers of days from 1 to 730 showing the distribution of victims for each repeat offence over time.

3.4.7. Power Few – Demographics

In the original dataset, age (at the time of offence), gender, ethnicity, nationality, and country of birth were extracted as variables against every crime. Table 8 below demonstrates the proportion of crime records where the respective data is unknown or unstated/undeclared by the victim. By way of example, in 2014, 85% of victims had their gender recorded as unknown or unstated; highlighting a data quality issue.

Table 8. Demographic data against all crime records 2014-2019

	Proportion of Victims with an 'Unknown' or 'Unstated' in each category				
	Gender	Ethnicity	Age	Nationality	Country of Birth
2014	84.57%	12.52%	1.83%	99.84%	100.00%
2015	82.63%	16.16%	2.19%	99.75%	100.00%
2016	80.89%	19.53%	1.98%	99.71%	100.00%
2017	78.95%	19.53%	2.63%	99.61%	100.00%
2018	63.82%	25.88%	2.60%	93.73%	99.99%
2019	3.07%	41.00%	2.23%	68.72%	99.97%

As a result of the lack of demographic data, ethnicity, nationality and country of birth were excluded from analysis in their entirety. Gender and age were both analysed in 2019 as in addition to table 8, the first five years of age data had a specific data quality issue with large numbers of negative ages, ages in excess of 150 and numerous ages not recorded as whole numbers. A pivot table was used to demonstrate the distribution of the PF across all ages and the ages were banded with ten-year intervals, starting at 0 to 9 years, then 10 to 19 years and so on. A pivot table was then inserted to tabulate the distribution of the PF for both harm and count at the respective PF threshold for both gender and age. This established the proportion of cumulative harm suffered by gender and age bands and the comparative mean harm scores. As a result of initial checks, independent-samples t-tests assuming unequal variance were conducted to compare males versus females in the PF and the PF versus NPF for age.

3.4.7. Victim-Offender Overlap

Victim-Offender Overlap

Analysis was conducted against the combined victim and offender datasets to establish what proportion were unique victims and unique offenders, and what proportion were victim-offenders using the VLOOKUP function on the URNs. This is demonstrated by Table 9 below. Victim-Offenders are those individuals who within the 6-year data set have been both a victim and an offender.

Table 9. Victims, Offenders and Victim Offenders

Category	Count
Victims	380,169
Offenders	52,448
Unique Victims	354979
Unique Offender	27259
Victim-Offenders	25189

Victim-Offender Power Few

All victims and offenders had their cumulative harm scores totalled against their URNs using pivot tables and using the above methodology, the PF was established for the victim and offender cohorts based on 80% harm. Similarly, the PF by count was established, with repeat victims/offenders being the PF. The PF and NPF were then coded with a '1' and '0' respectively. The proportions of PF victims that were also NPF offenders; PF offenders that were also NPF victims; and those that were both PF victims and PF offenders were then calculated. The respective combined harm scores were totalled and cumulatively summed under each of these categories and analysed as a proportion of total victim-offender harm from the two datasets.

Victim-Offender Onset Age

Using a minimum formula ('MIN') in Excel against the URN and 'Victim Age (at time of offence)' variables, the earliest age that each individual was first victimised was calculated and then repeated for the offender dataset. Using a count of URNs in a pivot table against every age in the dataset, proportions of individuals that were first victimised at every age were recorded and then repeated for offenders. For victim-offenders, their earliest age for victimisation and offending were identified and the older of the two ages were selected to indicate the onset of the VOO. As above, a pivot table was used to provide a count against each age to map out onset ages. As the age of criminal responsibility in England and Wales is 10, this was the starting point used.

3.5. Ethical Considerations

Following pseudonymisation, no attributable personal information has been processed as part of this analysis and no further ethical considerations have been identified.

3.6. External Validity

Kent Police's jurisdiction spans 1443 square miles, bordering London, Essex, Sussex and Surrey (HMICFRS n.d.). Kent has a population of approximately 1.86 million and is the gateway to Europe with three major ports, the Channel Tunnel, Lydd airport, numerous airfields and one of the busiest road networks in the country (Kent County Council 2021; Medway Council 2019; Kent Police 2020).

The Kent population is 51% female and 49% male with the largest ethnic group being white at 93.7%, the single largest minority group in Kent is Indian; representing 1.2% of the population. Approximately 60.8% of the Kent population are aged between 16 and 64, with 20.2% aged 65 and over (Kent County Council 2021).

4. Results

4.1. Introduction

This chapter details the results of the analysis. The first section establishes that there are consistent concentrations of victims suffering high-harm and that harm is more concentrated than count. The second section covers the versatility of victims, demonstrating that most PF victims suffer across crime types. The third section focuses on how accurately the PF concentrations can be used to predict future high-harm victimisations. This survival analysis identifies that survival in the PF is limited but that these concentrations can be used for prediction in other ways. Within this section, the optimal unit of time and concentration of harm/count for accurate prediction are explored with annual cohorts suffering 10% of harm/count producing the greatest accuracy.

The next section reports on patterns within the distribution of crime including escalation of harm, which is rare; conditional probability of a further offence, which increases with each repeat; frequency of repeat victimisation, which increases with each repeat; and variance based on demographics, with differences in the PF compared to the NPF by gender and age. The final section evidences the disproportionate harm attributable to the VOO and establishes the onset age, which follows the offender age-crime curve.

4.2. Power Few

Annual Patterns of Concentrations

Power Few – Harm

Between 2014 and 2019, 380,169 victims suffered 677,361 crimes, with a harm score totalling 74,320,040. The rank ordered harm scores were calculated cumulatively with the distribution plotted on a graph along with the distributions for each discreet year, as shown in figure 2. Each of these distributions represents a Power Curve. Over the six-year period, 3.4% of victims suffered 50% harm and 14.4% suffered 80% of all harm.

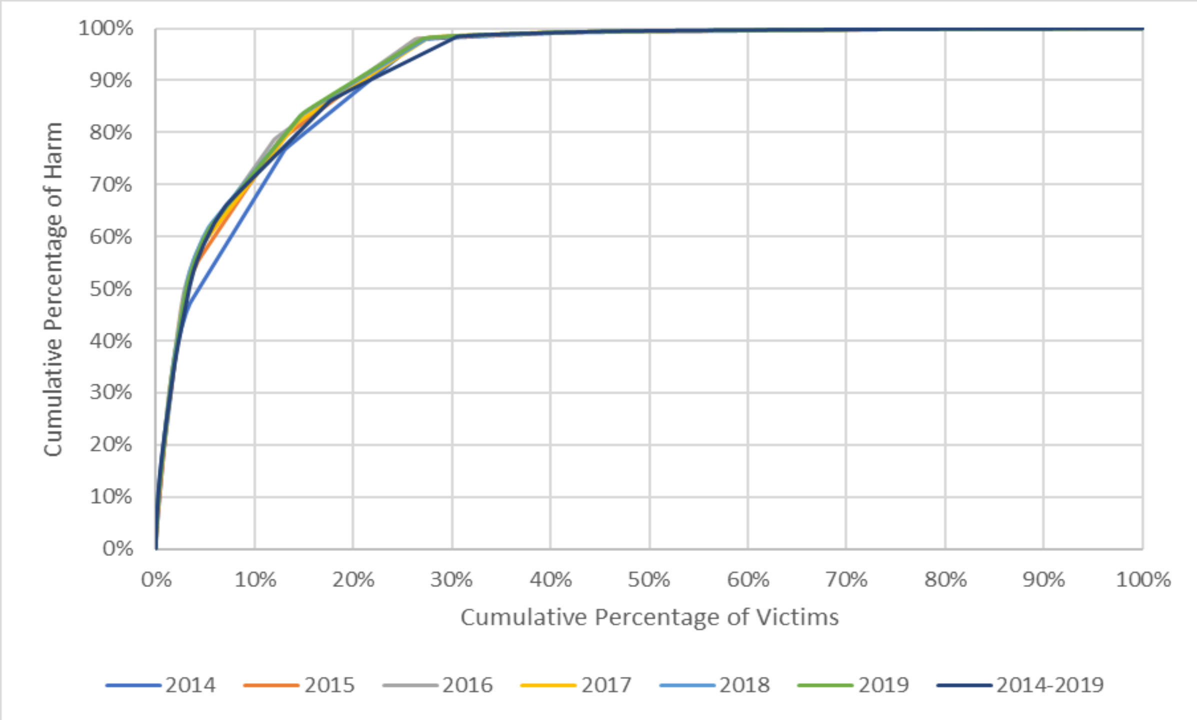


Figure 2. Victim Harm Distribution Across Years

Consistency in the Shape of the Distribution – Harm

Figure 2 demonstrates that despite some variance, there is strong consistency in the shape of the distribution year-to-year. As the point of inflection varies amongst the distributions, thresholds were applied as detailed in the methodology; these are detailed in Table 10 below. The mean number of victims across the six years who cumulatively suffered 10% of total harm was 249 per year (SD=19), this made up between 0.23% and 0.38% of a year's victim population. At 50% of total harm the mean number of victims per year was 2,735 (SD=428.3) and between 2.94% and 4.37% of the victim population and at 80%, there were 11,410 victims (SD=1956.9); between 12.93% and 15.15%.

CCHI Totals and Harm Ratios

Table 10 illustrates the respective harm ratios between the PF and NPF for each year against the different PF thresholds, as well as the cumulative harm scores suffered by the PF victim cohorts.

Table 10. Power Few Distributions with Harm Scores and Harm Ratios

Year	Percentage of Cumulative Harm (PF Threshold)	Cumulative Harm Score at Threshold	Percentage of Victim Population (PF)	Number of Victims in PF	PF Mean Harm Score	NPF Mean Harm Score	PF vs NPF Harm Ratio
2014	10%	783955	0.38%	250	3135.82	107.31	29:1
	50%	3912528.5	4.37%	2877	1359.93	61.12	22:1
	80%	6260090	15.15%	9981	627.2	28.01	22:1
2015	10%	874652.5	0.37%	247	3541.1	117.25	30:1
	50%	4372702	3.21%	2163	2021.59	67.05	30:1
	80%	6995667.5	13.61%	9169	762.97	30.06	25:1
2016	10%	1037115.5	0.30%	226	4589.01	122.97	37:1
	50%	5173902	2.94%	2234	2315.98	70.19	33:1
	80%	8277815.5	12.93%	9822	842.78	31.31	27:1
2017	10%	1409543.25	0.26%	248	5683.64	135.13	42:1
	50%	7046747.75	3.09%	2908	2423.23	77.27	31:1
	80%	11274660.25	13.50%	12708	887.21	34.63	26:1
2018	10%	1627492	0.23%	238	6838.2	144.13	47:1
	50%	8135425.75	3.05%	3107	2618.42	82.41	32:1
	80%	13017100.75	13.26%	13508	963.66	36.85	26:1
2019	10%	1566144.5	0.28%	283	5534.08	141.04	39:1
	50%	7823711.5	3.12%	3123	2505.91	80.65	31:1
	80%	12516627.5	13.26%	13274	942.94	36.04	26:1

As illustrated within Table 10, the range of harm ratios between the six years evidences that the PF (10%) suffered between 29 and 47 more harm than the NPF. At a 10% harm threshold, the mean harm score for a PF victim is 4,887 (SD=1401.96) compared to a NPF mean harm score of 128 (SD=14.49). At a 50% harm threshold, PF victims suffer between 22 and 33 times more harm than the NPF, with a PF mean harm score of 2207.5 (SD=462.42) compared to 73.1 (SD=8.36) for the NPF. Interestingly, at an 80% harm threshold, the range is similar to the 50% threshold with between 22 and 27 times more harm suffered by the PF with respective mean harm scores of 837.8 (SD=125.95) and 32.8 (SD=3.55).

Across the six years, the PF (10%) victims cumulatively suffered a mean annual total harm score of 1,216,484.8 (SD=364,572.38). At the 50% threshold the mean cumulative harm score suffered was 6,077,502.9 (SD=1,823,934.28) and at 80% it was 9,723,660.3 (SD=2,918,278.53).

Power Few by Units of Time – Harm

These PF concentrations were found across different units of time including years, bi-annuals, quarters and months. The results of the analysis across all of these units of time at the 10% and 80% total harm thresholds, incorporating the cumulative harm scores for the PF, mean harm scores and harm ratios between the PF and NPF, can be found in Appendix D. Table 11 below demonstrates the mean number of victims and range in the proportion of the victim population attributable to the PF by units of time.

Table 11. Power Few Harm Distributions by Unit of Time

	Unit of Time	Mean No. of Victims in the PF	Range of Victims in the PF
80% Harm	Bi-Annuals	6929 (SD=438.10)	12.54% - 13.15%
	Quarters	3709 (SD=133.50)	12.07% - 13.36%
	Months	1284 (SD=80.79)	11.55% - 12.78%
10% Harm	Bi-Annuals	152 (SD=16.57)	0.23% - 0.3%
	Quarters	92 (SD=6.63)	0.28% - 0.34%
	Months	36 (SD=2.95)	0.28% - 0.37%

For the PF (80%), these results establish that whilst the proportion of PF victims remains largely the same, months represent the unit of time where the concentration of harm is suffered by the smallest proportion of victims. Bi-annuals by contrast produce the smallest range in the proportion of victims in the PF with a variance of 0.61% across the six time-periods, making this the most consistent pattern of distribution. When considering the PF (10%), these results highlight real consistency across all units of time in terms of the proportion of victims suffering 10% of total harm. Quarters have the lowest variance with a range of 0.6%, followed by bi-annuals with a range of 0.7%.

Table 12 below illustrates the mean harm scores across the PF and NPF for the respective units of time which further depicts the consistency across different dyads. Table 12 also shows the mean harm ratios between the PF and NPF. The greatest disparity in mean harm scores between PF and NPF victims at 10% is seen in the bi-annuals, closely followed by annuals with respective mean harm ratios of 38:1 (SD=6.56) and 38:1 (SD=6.99). Conversely, at 80% total harm, months highlight the greatest difference in harm scores between the PF and NPF with a mean harm ratio of 29:1 (SD=1.14), followed by quarters, bi-annuals and then years, where the mean harm ratio is 25:1 (SD=1.58). Across all time periods the substantial disproportionality of harm concentrated on the PF is evident, with the distribution mirroring Power Few patterns found in previous research (Dudfield et al. 2017; White 2018).

Table 12. Power Few vs Non-Power Few Harm Scores by Units of Time

Threshold of Total Harm	Unit of Time	Mean of the PF Mean Harm Score	Mean of the NPF Mean Harm Score	Mean of PF vs NPF Harm Ratio
80%	Years	837.79 (SD=125.95)	32.82 (SD=3.55)	25:1 (SD=1.58)
	Bi-Annuals	885.70 (SD=37.46)	32.78 (SD=0.99)	27:1 (SD=0.53)
	Quarters	862.58 (SD38.16)	31.03 (SD=0.47)	28:1 (SD=1.32)
	Months	828.48 (SD=58.50)	28.77 (SD=1.15)	29:1 (SD=1.14)
10%	Years	4886.98 (SD=1401.96)	127.97 (SD=14.49)	38:1 (SD=6.99)
	Bi-Annuals	5087.09 (SD=656.17)	128.84 (SD=4.02)	38:1 (SD=6.56)
	Quarters	4357.32 (SD=400.27)	122.41 (SD=1.70)	36:1 (SD=3.06)
	Months	3770.46 (SD=523.02)	114.06 (SD=4.85)	33:1 (SD=3.44)

Power Few – Count

The six-year distribution of crime count was plotted along with the six discreet year distributions independent of one another as shown in figure 3. Over the course of the six-year period, 114,774 repeat victims made up 30.19% of all victims and suffered 60.82% of crimes. In turn, 43.12% of crimes were suffered by victims who had suffered three of more offences, and 21.74% was suffered by those who had six or more victimisations, amounting to 14,562 victims or 3.83% of the victim population. The twenty-five most victimised individuals representing 0.0066% of the victim population, suffered a total of 2937 crimes between them in six years; the minimum being 60 and the maximum being 957, with a mean of 117.48 (SD=175.94).

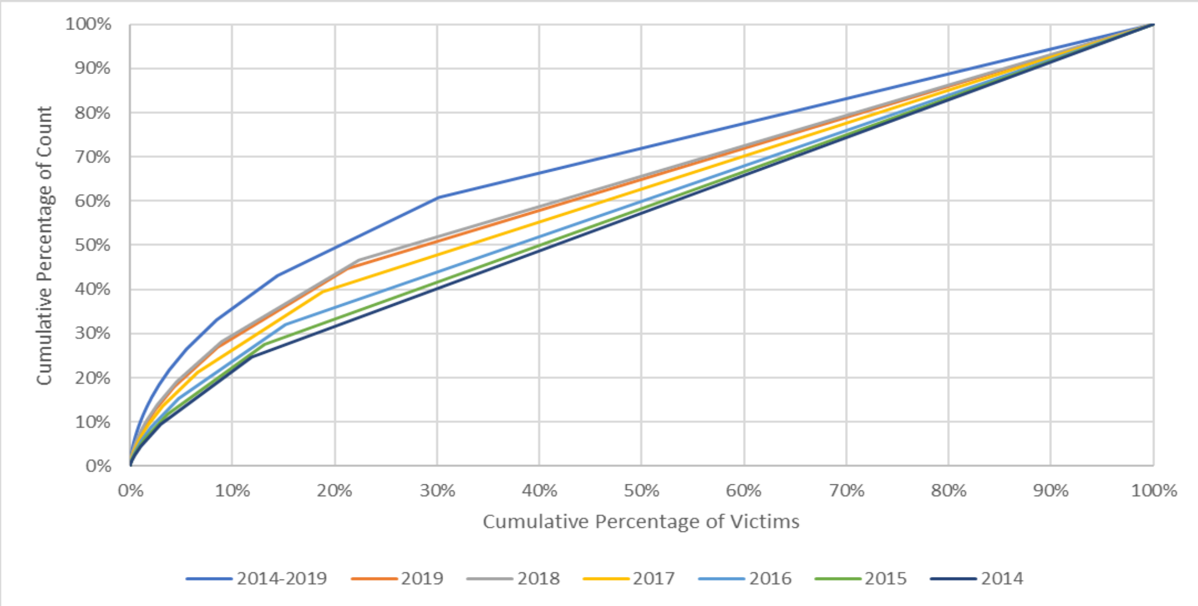


Figure 3. Victim Count Distribution Across Years

Consistency in the Shape of the Distribution – Count

As seen in figure 3, for the discreet six years, this single offence pattern is suffered by a range between 77.62% and 88.11% of the victim population. Whilst the pattern of distribution is consistent, the variance is evidenced in Table 13 below. Over the 6 years, the PF (10%) equates to a mean of 1,912 victims per year (SD=260.52), amounting to 1.55%-3.3% of the victim population. This PF consistently became more concentrated with fewer victims year-on-year in the cohort, suffering a greater proportion of victimisations. In the PF (Repeats), there was a mean of 15,138 victims (SD=6230.19) with range of between 11.89%-22.38% of the victim population. Interestingly, the number of repeat victims year-on-year correlates with the increases in recorded crime. Appendix E details the number of victims year-on-year that are repeats and the number of offences they cumulatively suffer. This has fluctuated over time, however from 2017 to 2019 between 22.38% and 25.54% of victims are repeats, suffering between 39.46% and 46.63% of crimes.

Count Totals and Ratios

Table 13 also highlights the cumulative harm scores of the PF and respective harm ratios between the PF and NPF. As identified in the methodology, unlike harm (Table 10), rather than having those victims suffering 80% of crimes, repeat victims have been used as a PF cohort because 80% of crimes would include single-offence victims.

Table 13. Power Few Distributions with Counts and Count Ratios

Period of Time	PF Threshold	Cumulative Victimisations at Threshold (& Total %)	% of Victim Population (PF)	Number of Victims in PF	PF Mean Victimisations	NPF Mean Victimisations	PF vs NPF Count Ratio
2014	10%	8059 (10%)	3.30%	2276	3.5	1.1	3.3:1
	Repeat	19891 (24.68%)	11.89%	8192	2.4	1	2.4:1
2015	10%	8360 (10%)	2.98%	2076	4.0	1.1	3.6:1
	Repeat	23050 (27.56%)	13.15%	9175	2.5	1	2.5:1
2016	10%	9722 (10%)	2.55%	1985	4.9	1.2	4.2:1
	Repeat	31159 (32.04%)	15.20%	11841	2.6	1	2.6:1
2017	10%	12744 (10%)	1.99%	1892	6.7	1.2	5.5:1
	Repeat	50299 (39.46%)	18.83%	17899	2.8	1	2.8:1
2018	10%	14751 (10%)	1.55%	1577	9.4	1.3	7:1
	Repeat	68813 (46.63%)	22.38%	22706	3.0	1	3:1
2019	10%	14088 (10%)	1.68%	1663	8.5	1.3	6.5:1
	Repeat	62993 (44.69%)	21.23%	21012	3.0	1.0	3:1

This table demonstrates that across six years the PF (10%) suffer a mean cumulative count of 11,287 victimisations (SD=2,946.33) with a year-on-year increase except for 2019. Repeat victims by contrast suffer a mean cumulative count of 42,701 (SD=20,933.26) with similar increases year-on-year. Whilst the number of repeat victims increased in correlation to crime increases, the number of victims in the PF (10%) decreased. The PF (10%) suffered a range of between 3.3 and 7 times more crimes than the NPF with a mean count of 6.2 (SD=2.4). Repeat victims suffered between 2.4 and 3 times more offences with a mean count of 2.7 (SD=0.25). These ratios are less disparate when comparing count to harm above.

Power Few by Units of Time – Count

Concentrations of crime count amongst victims were consistently distributed across time and based on different units of time. Appendix F provides the data for repeat victims over time by years, bi-annuals, quarters and months, and details cumulative and mean harm scores and a count ratio between the PF to NPF.

Table 14 displays the mean number of PF (repeat) victims and the range of the proportion of victim population that makes up the PF by units of time. The greatest consistency in terms of the proportion of the victim population constituting the PF can be seen in the smaller units of time, with greater variance as the unit of time increases, with *years* having the greatest variance of 10.49% compared to a variance of 1.48% for *months*. Compared to harm, there is less consistency in the concentration of victims suffering greater proportions of crime.

Table 14. Power Few (Count) Distributions by Unit of Time

	Unit of Time	Mean No. of Victims in the PF	Range of Victims in the PF
Repeat Victims	Bi-Annuals	9410 (SD=1663.48)	13.67% - 19.73%
	Quarters	4668 (SD=419.67)	14.71% - 17.18%
	Months	1198 (SD=115.01)	10.67% - 12.15%

Table 15 presents the PF and NPF mean harm scores for the four units of time highlighting that the greater the unit of time, the higher the concentration of crime in the PF. Annually, repeat victims are suffering 2.74 times the number of crimes as non-repeat victims. Due to the binary nature of the PF and NPF here, the NPF are always single-offence victims. Compared to harm, the disparity between the PF and NPF is not as substantial with a ratio of less than three-to-one compared to harm scores that had a ratio of up to 37.8:1.

Table 15. Power Few vs Non-Power Few Crime Counts by Units of Time

Threshold of Total Harm	Unit of Time	Mean of the PF Mean Crime Count	Mean of the NPF Mean Crime Count	Mean of PF vs NPF Crime Ratio
Repeat Victims	Years	2.74 (SD=0.25)	1	2.7:1
	Bi-Annuals	2.71 (SD=0.1)	1	2.7:1
	Quarters	2.57 (SD=0.05)	1	2.6:1
	Months	2.35 (SD=0.05)	1	2.4:1

Power Few – Harm vs Count

The distribution of victimisations is less concentrated than harm, for example the mean proportion of the victim population suffering 10% of total harm across six years is 0.3%, compared to 2.34% for count.

Table 16 below demonstrates the total number of victims in the PF Harm Cohort (80% harm) and PF Count Cohort (Repeats). A total of 35,492 victims were in both the PF Harm and PF Count cohorts, amounting to 9.3% of the victim population. Twice the proportion of PF Harm victims were in this combined cohort showing that a greater proportion of PF harm victims are also in the PF count than vice versa.

Table 16. Power Few - Harm and Count

	Number of Victims	Percentage of All Victims	Percentage of Combined PF Harm and PF Count Cohort
PF Harm Cohort (Suffer 80% of Total Harm)	54747	14.40%	64.83%
PF Count Cohort (Suffer Repeat Victimisation)	114774	30.19%	30.92%
Combined PF Harm and PF Count Cohort	35492	9.34%	100%

4.3. Versatility

Figure 4 below takes each offence category and shows the proportion of PF Victims (80% Harm) that are 'one-timers'; suffering only one high-harm offence, specialists or generalists against each one.

The graph is rank ordered based on percentage of PF harm under the specialist category. Figure 5 replicates this for the PF Count (Repeats), however by the nature of repeat victimisation 'one-timers' are non-existent.

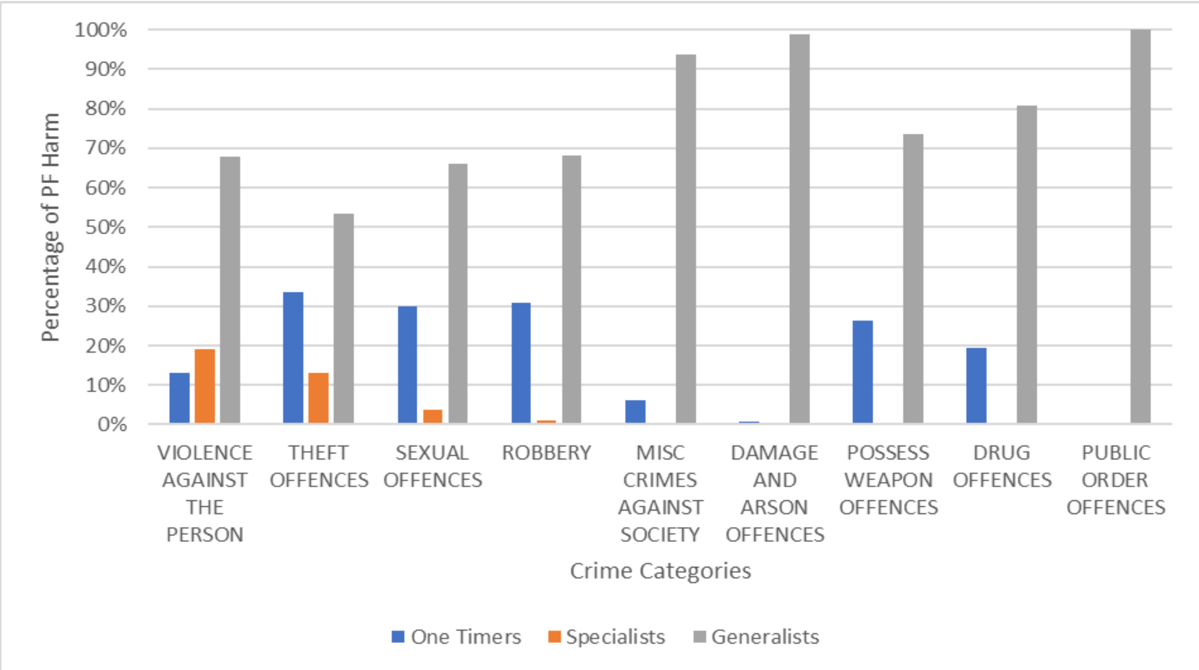


Figure 4. Versatility of Power Few Victim (Harm) by Crime Type

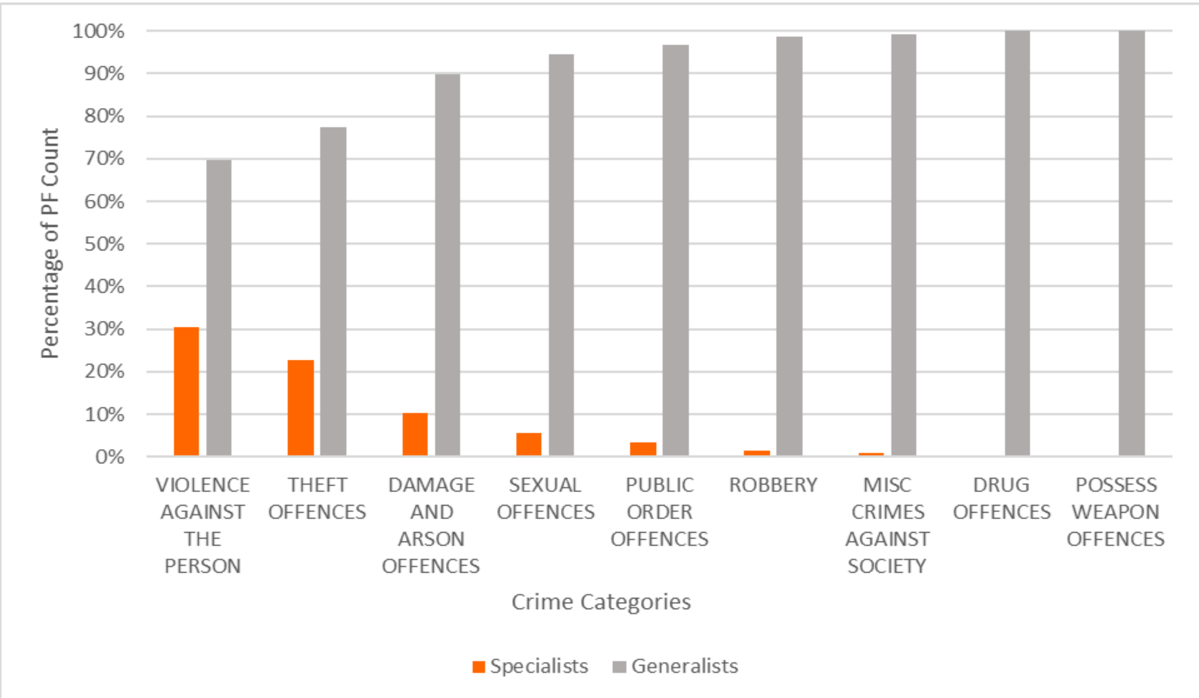


Figure 5. Versatility of Power Few Victim (Count) by Crime Type

It is apparent that the PF (Harm) specialists are concentrated in several offence categories whereas 'one-timers' and generalists are more widely distributed across crime categories. The PF (Harm) 'one-timers' account for 35.18% of victims and 20.3% of crimes suffered by the PF cohort with generalists being widely distributed across crime categories. For both harm and count, violence saw the greatest proportion of 'specialists', with a total of 5935 victims (19.21%) from the PF (harm) suffering only violent offences, compared to 25,102 victims (30.43%) from the PF (count). For both harm and count, theft was the second highest 'specialists' category before divergence between the two cohorts.

4.4. Power Few – Survival Analysis

Survival Across Six Years by Unit of Time

Tables 17 and 18 below shows the survival rates of the different PF cohorts for harm and count by units of time, highlighting attrition from the initial cohorts.

Table 17. Power Few (Harm) Survival Over Time by Unit of Time

			Survival - Proportion of Victims											
	Unit of Time	Threshold	PF (P1)		P1 to P2		P2 to P3		P3 to P4		P4 to P5		P5 to P6	
			No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Harm	Years	10% Threshold	216	100%	17	7.87%	5	2.31%	2	0.93%	1	0.46%	1	0.46%
		80% Threshold	9456	100%	638	6.75%	172	1.82%	68	0.72%	39	0.41%	21	0.22%
	Bi-Annuals	10% Threshold	136	100%	10	7.35%	2	1.47%	2	1.47%	1	0.74%	0	0.00%
		80% Threshold	2798	100%	266	9.51%	66	2.36%	22	0.79%	10	0.36%	5	0.18%
	Quarters	10% Threshold	75	100%	1	1.33%	0	0.00%	0	0.00%	0	0.00%	0	0.00%
		80% Threshold	3831	100%	176	4.59%	40	1.04%	12	0.31%	4	0.10%	4	0.10%
	Months	10% Threshold	36	100%	0	0.00%	0	0.00%	0	0.00%	0	0.00%	0	0.00%
		80% Threshold	1393	100%	29	2.08%	3	0.22%	2	0.14%	0	0.00%	0	0.00%

Table 17 shows that for harm, survival rates within the PF from the first period to the second is always less than 10%, and from the second to third is less than 2.5%. Bi-annuals demonstrated the best survival rate at the 80% threshold and 'years' had the best survival rate at the 10% threshold.

For years, the PF (10%) evidenced a slightly reduced decay from the PF compared to the PF (80%), however the reverse is true for the other units of time.

Table 18. Power Few (Count) Survival Over Time by Unit of Time

			Survival - Proportion of Victims											
	Unit of Time	Threshold	PF (P1)		P1 to P2		P2 to P3		P3 to P4		P4 to P5		P5 to P6	
			No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Count	Years	Repeat Victims	1884	100%	554	29.41%	227	12.05%	138	7.32%	91	4.83%	67	3.56%
	Bi-Annuals	Repeat Victims	1876	100%	641	34.17%	306	16.31%	171	9.12%	97	5.17%	67	3.20%
	Quarters	Repeat Victims	1729	100%	407	23.54%	156	9.02%	86	4.97%	46	2.66%	27	1.56%
	Months	Repeat Victims	304	100%	52	17.11%	19	6.25%	10	3.29%	8	2.63%	5	1.64%

For count, as seen in Table 18, the rates of survival are far greater with bi-annuals evidencing the greatest survival across all periods of time, followed by annuals, quarters and then months. Less than 4% survive from the first period of time to the sixth across all units of time suggesting that the PF substantially change over time.

Of note, table 19 shows the mean rates of the initial PF reoccurring in any of the subsequent PF cohorts over the next five periods of time. This highlights that from the original PF, a small proportion appear in the PF again in subsequent periods of time, just not consistently and not necessarily the same unique victims, which is a barrier to prediction. Appendix G shows the full breakdown across all time periods and demonstrates a gradual decay over time.

Table 19. Mean Survival Rates of the PF for harm and count from Period 1 by Units of Time

	PF Threshold	Unit of Time	Mean No. of Victim	Mean % of Victim Population
Harm	10%	Years	9 (SD=4.85)	4.17%
		BiAnnuals	5.2 (SD=3.70)	3.82%
		Quarters	1.6 (SD=1.34)	2.13%
		Months	0.2 (SD=0.45)	0.56%
	80%	Years	484 (SD=91.93)	5.12%
		BiAnnuals	196.6 (SD=46.27)	7.03%
		Quarters	126.2 (SD=32.74)	3.29%
		Months	26.6 (SD=7.16)	1.91%
Count	Repeat Victims	Years	464.8 (SD=55.35)	24.67%
		BiAnnuals	465.8 (SD=119.57)	24.83%
		Quarters	282.8 (SD=80.55)	16.36%
		Months	30 (SD=14.37)	9.87%

Survival – Crime Types

When treating crime types in isolation, the PF follow a similar pattern of attrition with a steep initial decay before plateauing out. As seen in table 20, from one year to the next 'rape and sexual offences' is the category with the greatest survival rate from the first year to the second at 10%, followed by 'Violence-Injury' at 4.88%, compared to robbery where 0% survive in the PF. Violence-Injury is the only crime type with survival beyond three consecutive years or more.

Table 20. PF Survival Over Years by Crime Type

Year	Violence - Injury		Violence - No Injury		Rape & Sexual Offences		Robbery	Residential Burglary
	PF Harm (80%)	PF Count (Repeats)	PF Harm (80%)	PF Count (Repeats)	PF Harm (80%)	PF Count (Repeats)	PF Count (Repeats)	PF Count (Repeats)
2014	1538	720	102	1203	40	79	16	160
2015	75	60	1	122	4	5	0	4
2016	15	11	0	36	1	0	0	1
2017	3	4	0	0	0	0	0	0
2018	2	3	0	0	0	0	0	0
2019	2	1	0	0	0	0	0	0

PF Survival – Top 100

Focusing on the highest harmed group, the top 100 most harmed victims' continued survival from 2014 to 2019 is illustrated in Table 21 below. This pattern of distribution year-on-year follows previous results with no victim remaining in the PF (Harm) for more than two consecutive years and only one victim from the PF (Count) remaining in all 6 years.

Table 21. Power Few Survival - Top 100

Survival Over Time	Harm	Count
2014	100	100
2015	9	13
2016	1	2
2017	0	1
2018	0	1
2019	0	1

When replicated from one year to the next across the six years, the mean survival rate from the top 100 most harmed into the second year was 7.2 compared to 17.8 for count.

Survival – Period to Period by Units of Time

Replications of survival analysis from one period of time to the next was conducted five times for harm and count across each unit of time, with the full analysis available in Appendix H. Table 22 below demonstrates the mean survival rates of this analysis.

Table 22. Mean Survival Over Time

<table>
<tr><th></th><th>PF Threshold</th><th>Unit of Time</th><th>Mean Survival (% of PF)</th></tr>
<tr><td rowspan="8">Harm</td><td rowspan="4">10%</td><td>Years</td><td>6.99%</td></tr>
<tr><td>Bi-Annuals</td><td>6.15%</td></tr>
<tr><td>Quarters</td><td>2.43%</td></tr>
<tr><td>Months</td><td>0.00%</td></tr>
<tr><td rowspan="4">80%</td><td>Years</td><td>9.90%</td></tr>
<tr><td>Bi-Annuals</td><td>9.89%</td></tr>
<tr><td>Quarters</td><td>6.40%</td></tr>
<tr><td>Months</td><td>2.20%</td></tr>
<tr><td rowspan="4">Count</td><td rowspan="4">Repeat Victims</td><td>Years</td><td>34.72%</td></tr>
<tr><td>Bi-Annuals</td><td>30.82%</td></tr>
<tr><td>Quarters</td><td>22.63%</td></tr>
<tr><td>Months</td><td>15.06%</td></tr>
</table>

Table 22 highlights that across all PF concentrations, the greatest survival rates of the PF occur with 'years' as the unit of time, closely followed by bi-annuals. The proportions decrease as the unit of time reduces and the survival of the PF for count is greater than for harm with the survival rate being 4.97 times greater for 'years'.

Survival – PF and the NPF

Based on the greater stability of the PF from year-to-year, analysis was undertaken on different PF threshold victim cohorts from 2014 to identify what proportion of those victims subsequently suffered further victimisation over consecutive years, regardless of whether they remained in the PF cohort. Figure 6 illustrates the results for harm and includes comparative survival analysis for all victims generally and PF victims remaining in the PF.

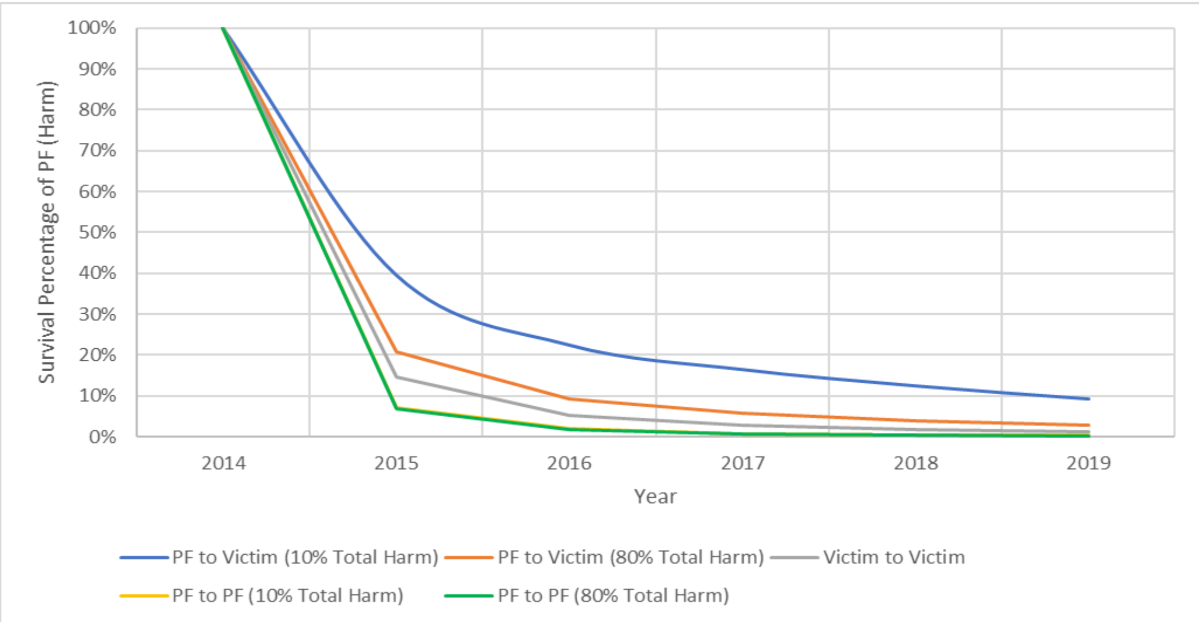


Figure 6. Survival Rates of PF Victims and Victims by Cohort Membership – Harm

The consistency of the victims' participation in each cohort declines over time with an initial steep decay. The rate of attrition is lowest when considering those that were originally in the PF and went on to be subsequent victims, regardless of whether or not they were in the PF. The same pattern is seen for count in Figure 7 below.

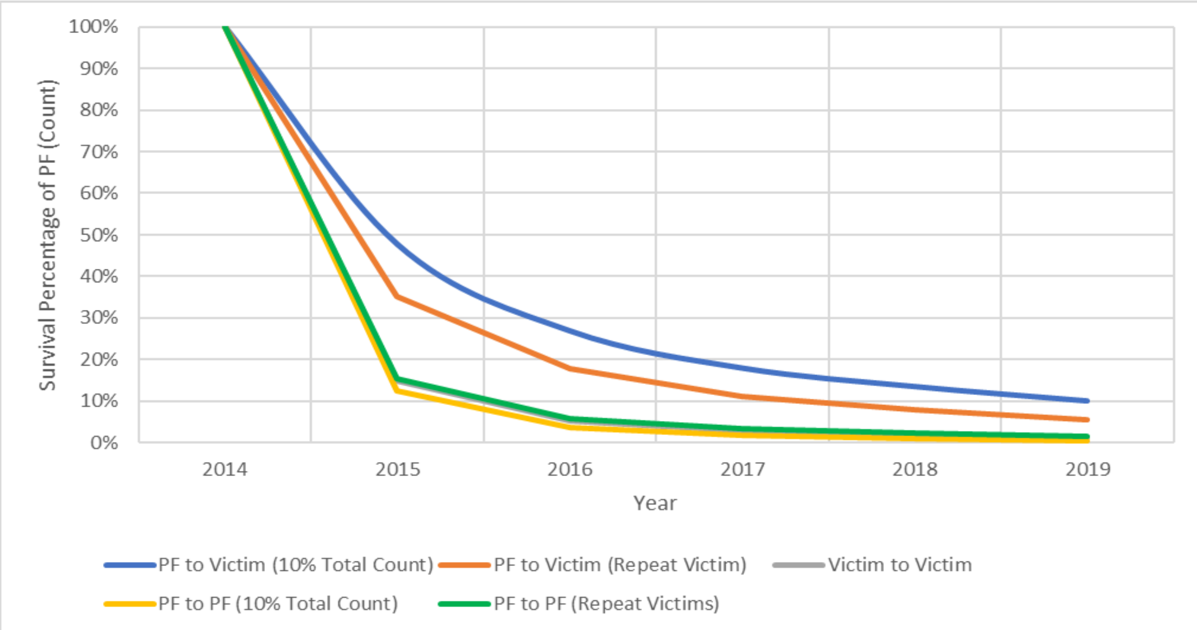


Figure 7. Survival Rates of PF Victims and Victims by Cohort Membership – Count

Table 23 focuses specifically on the cohorts of PF Victims from 2014 who go on to be victimised again in 2015 regardless of their membership in the PF. Table 23 highlights the mean harm scores/counts as well as the ratio compared to the mean victim harm/count for that year, taken from the full breakdown of every year for these cohorts, detailed in Appendix I.

Table 23. PF to Victim Cohort Survival 2014 - 2015 with Mean Harm Scores / Count and Harm Ratios

	Power Few Threshold	Year	Number of Victims in Cohort	% of Victim Population	Percentage Survival	Cohort Mean Harm Score / Count	Victim Population Mean Harm Score / Count	Harm/Count Ratio (Cohort to Victim Population)
Harm	10% Total Harm	2014	250	0.38%	NA	3135.82 (SD=1797.8)	118.8 (SD=359.2)	26.4:1
		2015	99	0.15%	39.60%	1357.78 (SD=3127.32)	129.9 (SD=404.2)	10.5:1
	80% Total Harm	2014	9981	15.15%	NA	627.2 (SD=725.07)	118.8 (SD=359.2)	5.3:1
		2015	2081	3.09%	20.85%	358.91 (SD=952.97)	129.9 (SD=404.2)	2.8:1
Count	10% Total Count of Victimisations	2014	2276	3.30%	NA	3.54 (SD=1.67)	1.17 (SD=0.6)	3:1
		2015	1085	1.56%	47.67%	2.43 (SD=2.9)	1.19 (SD=0.7)	2:1
	Repeat Victims	2014	8192	11.89%	NA	2.43 (SD=1.12)	1.17 (SD=0.6)	2.1:1
		2015	2890	4.14%	35.28%	1.99 (SD=2.09)	1.19 (SD=0.7)	1.7:1

Based on single year-to-year survival, the more concentrated the harm and crime, namely, the PF (10%) cohorts, the greater the survival. Of the PF (10% harm) cohort, 39.6% are then victimised the following year, irrespective of whether they are in the PF or not and importantly, they suffer a mean of 10.5 times more harm than the mean of the victim population. For count, there is a greater comparative survival rate from the PF (10%), however the count ratio is less substantial with the mean count being double that of the complete victim population for that year.

Figure 8 below shows comparative sensitivity and specificity analyses between the 'PF to Victim' and 'PF to PF' cohorts including the respective positive and negative prediction values. Targeting of the PF on the basis that they will remain in the PF offers only a 7.2% positive prediction rate, however, when looking at further harm suffered in the subsequent year irrespective of PF membership, the rate of survival is much higher at 39.6%. The sum of false negatives, where victims are harmed when they were not predicted to be, is a concern, however this approach remains better than not forecasting and preventing harm at all.

Power Few to Victim

	Re-Victimised	Not Re-Victimised
PF Victim Predicted to be Re-Victimised	99 (True Positive)	151 (False Positive)
NPF Victim Predicted to Not be Re-Victimised	9378 (False Negative)	56241 (True Negative)
Positive Prediction Value	39.60%	
Negative Prediction Value	85.71%	

Power Few to Power Few

	Re-Victimised	Not Re-Victimised
PF Victim Predicted to be Re-Victimised	18 (True Positive)	232 (False Positive)
NPF Victim Predicted to Not be Re-Victimised	9378 (False Negative)	56241 (True Negative)
Positive Prediction Value	7.20%	
Negative Prediction Value	85.71%	

Figure 8. Comparative Sensitivity and Specificity Analyses

4.5. Power Few – Escalation

Table 24 demonstrates an initial breakdown of repeat crimes across the six years for the entire victim population as well as by the PF and NPF. Detailed within the table are the number of those repeats that see an escalation in harm, de-escalation or 'no change' in the harm. The number of escalations and de-escalations are largely equal and are both greater in the PF with less static harm scores.

Table 24. Escalation and De-Escalation in Harm Scores

	All Victims	PF (80%)	NPF
Number of Repeat Crimes	296858	147457	149401
% of Crimes that are Repeats	43.90%	73.04%	31.50%
Number of Escalations	104789	55248	49541
Escalations as % of Repeats	35.30%	37.47%	33.16%
Number of De-escalations	103938	55333	48605
De-escalations as % of Repeats	35.01%	37.52%	32.53%
Number 'No Change' in Harm Score	88131	36876	51255
'No Change' in Harm Score as % of Repeats	29.69%	25.01%	34.31%

Table 25 focuses on repeat escalation and highlights the number and proportions of PF and NPF victims that suffer a series of escalations. This is broken down by the number of repeat victimisations that are consecutive escalations (pure escalation) and those that escalate with intermittent victimisations of the same harm score as the prior offence. The table shows that although the PF are more likely to suffer escalation than the NPF, repeat escalation is very rare with no victims suffering five escalations and no more than 0.35% suffering three escalations.

Table 25. Repeat Escalation of Harm - Power Few and Non-Power Few

		Number of Escalations							
		2 Escalations		3 Escalations		4 Escalations		5 Escalations	
		No. of Victims	% of PF/NPF Population	No. of Victims	% of PF/NPF Population	No. of Victims	% of PF/NPF Population	No. of Victims	% of PF/NPF Population
Power Few	Pure Escalation*	7917	3.92%	696	0.34%	33	0.02%	0	0.00%
	Escalation Including No Change in Harm Score	707	0.35%	313	0.16%	10	0.00%	0	0.00%
Non-Power Few	Pure Escalation	3728	0.79%	169	0.04%	4	0.00%	0	0.00%
	Escalation Including No Change in Harm Score	202	0.04%	111	0.02%	2	0.00%	0	0.00%

*Pure Escalation refers to an escalation in the harm score with each consecutive repeat

4.6. Conditional Probability

Figure 9 shows the conditional probability of a victim suffering a further crime. The probability consistently increases following each prior offence, starting at a 20% probability of suffering an initial repeat through to a ninth repeat with a 68.5% probability. The probability then fluctuates as the low volumes start to create noise in the distribution. After suffering three repeats, it is more likely than not that a victim will suffer a further offence, at 53.5%. After nineteen repeats, only 26 victims continued to suffer further repeats.

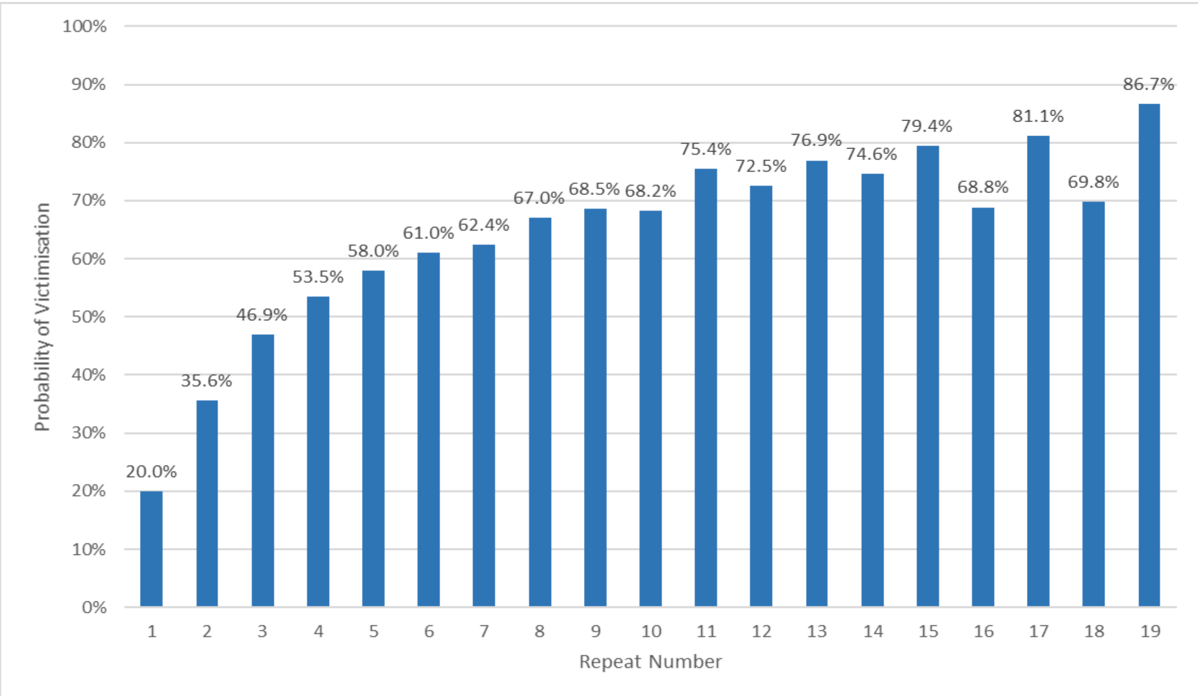


Figure 9. Conditional Probability of a Further Offence

4.7. Frequency of Repeat Victimisation

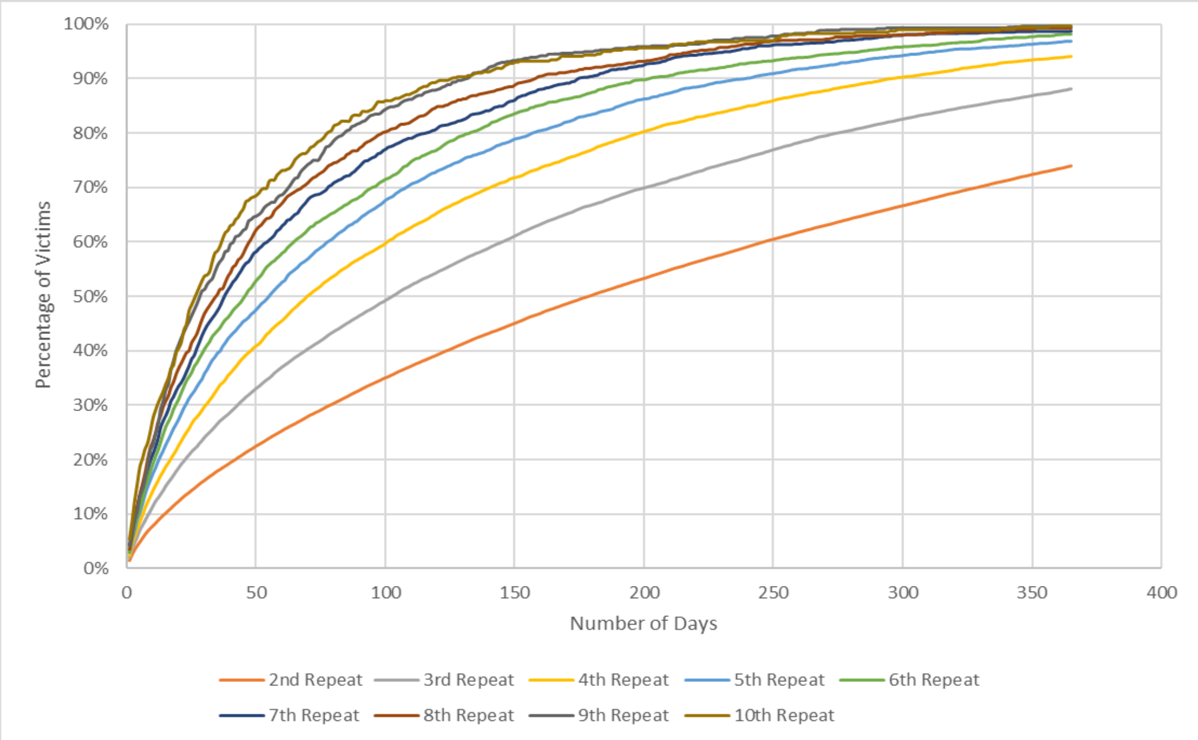


Figure 10. Frequency of each Repeat Victimisation

Figure 10 illustrates the frequency by which victims suffer each consecutive repeat. The respective proportions of victims suffering repeats over time is detailed in Appendix J. The data indicates that 9.82% of first repeats occur within 14 days and 11.04% of third repeats occur within 7 days of the last offence. Based on the aforementioned conditional probability data, with the probability of someone suffering a fourth repeat being more likely than not, this data highlights that 21.7% of fourth repeats occur within 14 days of the prior offence and 50.08% occur within 55 days. Further repeats have not been plotted as the sample size becomes smaller and the data becomes noisy.

4.8. Power Few – Demographics

Gender

Table 26 sets out the number of victims by gender comprising the PF and NPF cohorts based on the harm and count thresholds. At the 10% threshold for harm and count, females are disproportionately represented in the PF with a gender ratio of 2.8:1 for harm and 1.7:1 for count. At the 80% threshold, a greater proportion of the PF by harm are men (ratio of 1.1:1) and a greater proportion for count are women (ratio 1.3:1).

Table 26. Power Few and Non-Power Few by Gender

		Number of Victims			
		Male	Female	Unknown / Unstated	Cohort Total
Harm	PF (10%)	72	199	12	283
	NPF (10%)	48142	45276	6416	99834
	PF (80%)	6546	5983	747	13276
	NPF (80%)	41668	39492	5681	86841
Count	PF (10%)	603	1047	14	1664
	NPF (10%)	49010	46883	3069	98962
	PF (Repeats)	9141	11634	237	21012
	NPF (Repeats)	39869	35249	2832	77950

Figure 11 compares the distribution of cumulative harm between males and females in the PF Harm cohorts. Females collectively suffer greater levels of harm and when taking the greatest concentration of harm at the 10% threshold, this proportion sits at 78.13% of harm compared to 20.34% of harm suffered by males.

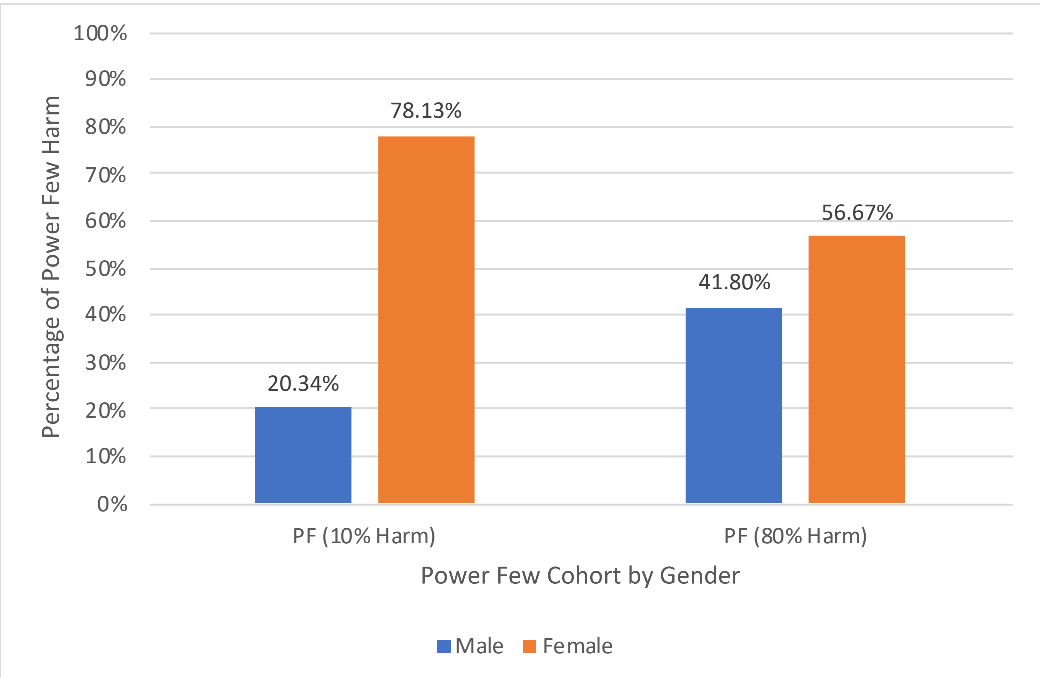


Figure 11. Distribution of Crime Harm by Gender for Power Few Cohorts

Figure 12 shows the same analysis of distribution but for count. It can be seen that the distribution is more evenly balanced than harm, however in the more concentrated cohort of count (10%), females suffer 61.52% of the count compared to 37.72% for males.

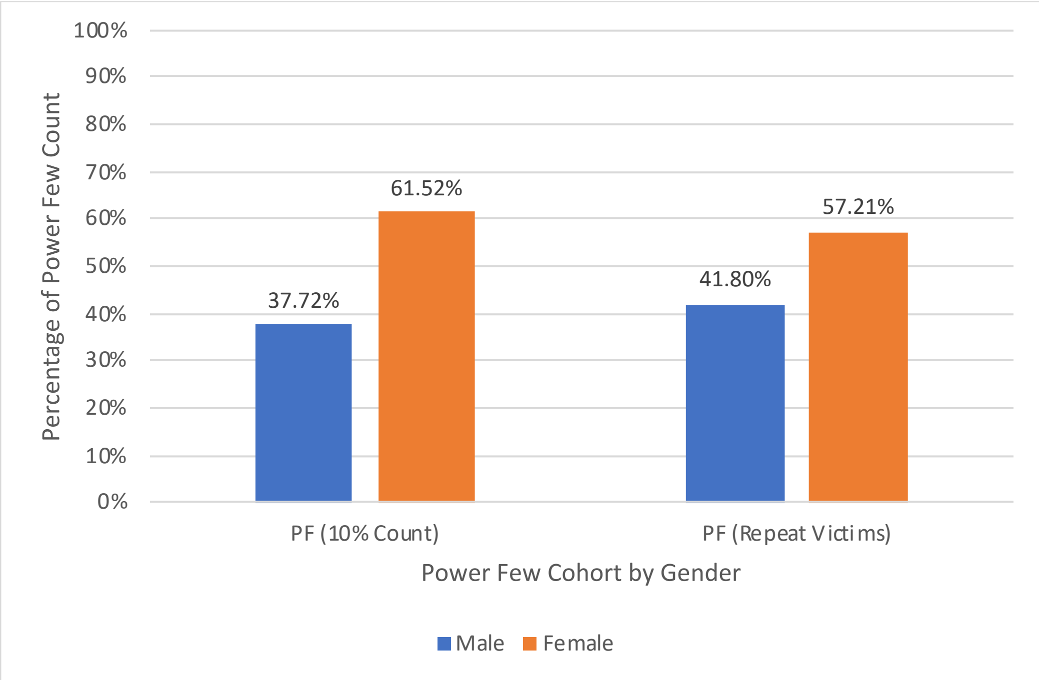


Figure 12. Distribution of Crime Count by Gender for Power Few Cohorts

Table 27 provides a comparison of mean harm scores. The pattern remains consistent in the highest harm threshold of 10% with more women being in the PF than men, with a greater cumulative harm and greater mean harm score with a ratio of 1.4:1. These distributions are more even for count.

Table 27. Mean Harm Scores and Harm Ratio for Power Few by Gender

		Mean Harm Score - Female)	Mean Harm Score - Male	Harm Ratio
Harm	PF (10%)	6051.39 (SD=3696.75)	4353.43 (SD=1076.57)	1.4:1
	NPF (10%)	152.15 (SD=439.35)	126.86 (SD=328.13)	1.2:1
	PF (80%)	1113.68 (SD=1421.06)	750.92 (SD=721.96)	1.5:1
	NPF (80%)	36.21 (SD=76.02)	36.12 (SD=77.12)	1:1
Count	PF (10%)	8.28 (SD=4.03)	8.82 (SD=8.48)	0.9:1
	NPF (10%)	1.37 (SD=0.79)	1.26 (SD=0.65)	1.1:1
	PF (Repeats)	3.1 (SD=2.19)	2.88 (SD=2.79)	1.1:1
	NPF (Repeats)	1 (SD=0)	1 (SD=0)	1:1

In addition to the comparative mean harm, statistical testing of the PF was conducted with females treated as the baseline group from which males were compared. A independent-samples T-Test assuming unequal variance was conducted for the PF (10% harm) showing that harm differs between males and females in the PF (10% harm) ($t=3.8$, $p<0.01$). For the PF (80% harm), a difference was also found ($t=17.8$, $p<0.01$). When compared to count, the PF (10%) saw no statistically significant difference between females and males ($p=0.15$), however, the PF (RV) did differ ($t=6.1$, $p<0.01$).

Age

Figure 13 shows a demonstrable difference with the PF (10%) being far more concentrated with the first peak at age 12 (2.54%) before the highest peak at 16 (5.07%) before lesser concentrations across ages. The NPF and PF (80%) are more comparable, albeit the PF (80%) still peaks at an earlier age than the NPF, with a greater proportion in the teenage years. The low numbers in the PF (10%) create fluctuations, however the distribution evidences that this cohort are younger than their counterparts.

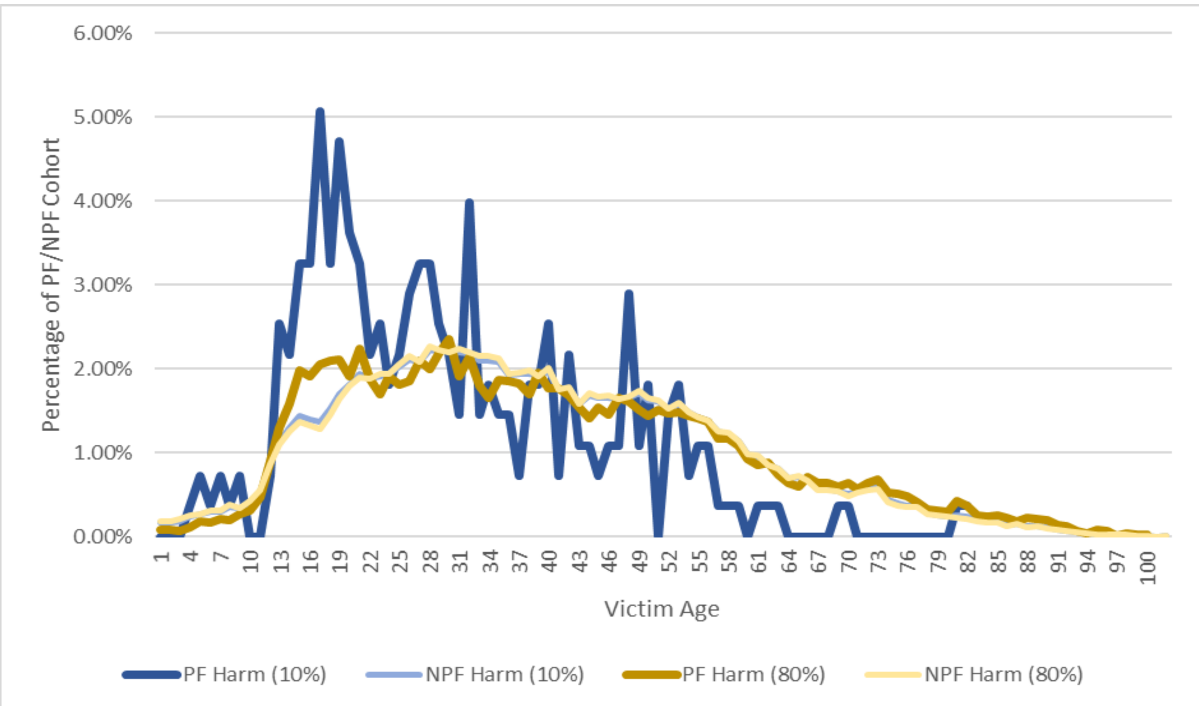


Figure 13. Distribution of Crime Harm by Age for the Power Few and Non-Power Few by PF Cohorts

Figure 14 plots the proportions of crime count suffered by PF and NPF victims by age. Compared to harm, the count distribution is more tightly clustered with a greater proportion of the PF aged between mid-teens and mid-forties. The PF and NPF cohorts are comparable with the greatest proportion of the PF (10%) at age 26 with 53 victims (3.19%) compared to age 28 with 580 (2.77%) for the PF (80%) and age 27 for both NPF (10%) and NPF (80%).

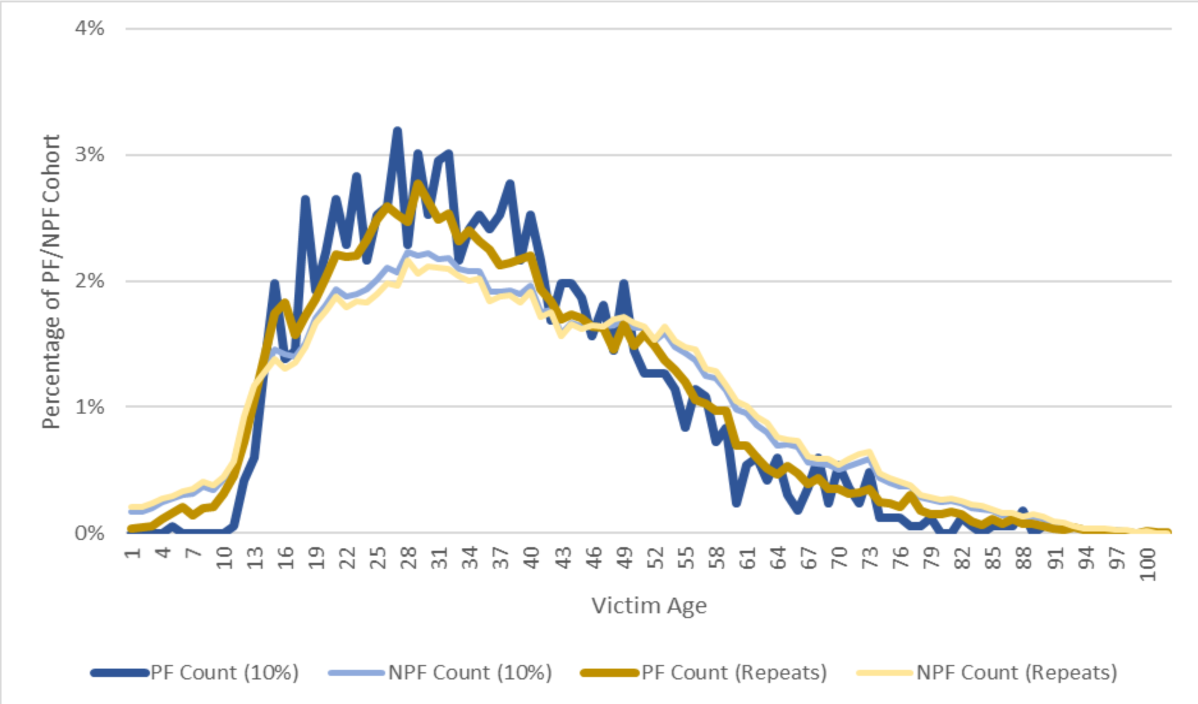


Figure 14. Distribution of Crime Count by Age for the Power Few and Non-Power Few by PF Cohorts

The full breakdown of the PF and NPF by age and PF threshold can be found in Appendix K, which includes the cumulative sums of harm and count, and the mean harm/count per victim. Table 28 below compares the PF (10%) harm and count cohorts using the mean harm/count per victim as these cohorts represent the greatest concentrations in age groups. The greatest mean harm per victim in the PF (10% harm) is in the age 80-89 bracket, which results from that sample size being made up of two victims with a mean harm score in excess of 6000. The next highest mean harm score is in the 10-19 bracket at 6053.84 followed by 30-39. Count sees the highest mean count in the 70-79 bracket followed by the 50-59 bracket. The greatest cumulative sum of harm for the PF (10% harm) is in the 10-19 age bracket and then the 20-29 bracket, for count (10%) the highest volume is in the 20-29 bracket and then 30-39 showing that greater harm is suffered by the PF earlier in life with greater volumes suffered later in life.

Table 28. Mean Harm/Count for the PF/NPF by Age

	Harm 10%		Count 10%	
	Mean Harm per Victim		Mean Count per Victim	
Age	PF	NPF	PF	NPF
0-9	5018.28	154.29	10	1.15
10-19	6053.84	208.27	7.86	1.33
20-29	5377.72	164.75	8.09	1.38
30-39	5772.59	131.30	8.24	1.36
40-49	5218.59	121.25	9.5	1.31
50-59	4613.95	102.19	8.85	1.26
60-69	5558.20	90.44	8.37	1.20
70-79	0.00	97.22	9.79	1.18
80-89	6752.50	119.74	8.1	1.16
90-99	0.00	146.77	0	1.11
100+	0.00	37.70	0	1.40

For the purposes of age-based statistical testing, independent-samples T-Tests assuming unequal variance were utilised, with the NPF treated as the baseline group from which the PF were compared. In addition to the difference between mean age, for the PF (10% harm), the difference was not statistically significant ($p=0.18$). It is worth noting that the sample size of the PF here amounted to 32 victims compared to 94,281 NPF victims. For the PF (80% harm), the mean age did show a difference between the PF and NPF ($t=2.6$, $p<0.01$). By contrast, for PF (10% count), there was a statistically significant difference between the PF and NPF in terms of age ($t=-8$, $p<0.01$). For the PF (80% count), there was again a difference between the PF and NPF ($t=-21.8$, $p<0.01$). Despite these statistical tests, the difference between the PF and NPF mean age was a maximum of four years and always in the mid-30s, which has limited value for operational targeting.

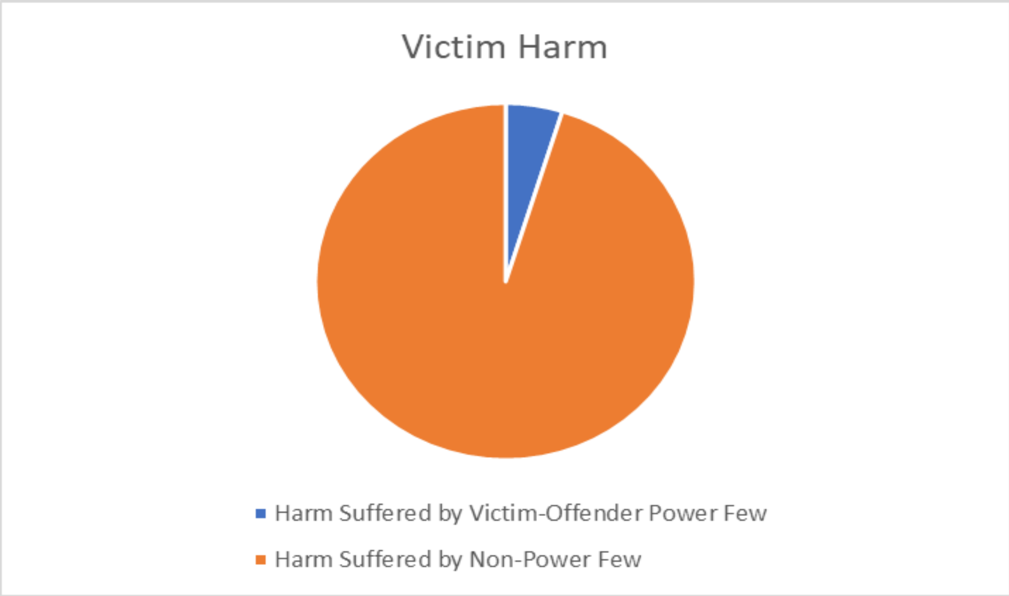
4.9. Victim-Offender Overlap

Table 29 shows the proportion of Victims, Offenders and Victim-Offenders against the combined victim and offender datasets. There are a total of 25,189 (6.18%) Victim-Offenders in the dataset, 2079 individuals (0.51%) that are both PF (harm) victims and PF (harm) offenders; PF Victim-Offenders, and 7370 (1.81%) PF Victim-Offenders when analysing count.

Table 29. Victim, Offender and Victim-Offender Proportions

	Percentage of Combined Victim and Offender Populations
Unique Victims	87.13%
Unique Offenders	6.69%
Victim-Offenders	6.18%
PF (80% Harm) Victim-Offenders	0.51%
PF (Count - Repeat) Victim-Offenders	1.81%

Figure 15 shows the proportion of victim harm these PF Victim-Offenders suffer and proportion of offender harm they commit. These 2079 (0.51%) individuals suffer a disproportionate 4.82% of victim harm and commit 20.58% of offender harm.



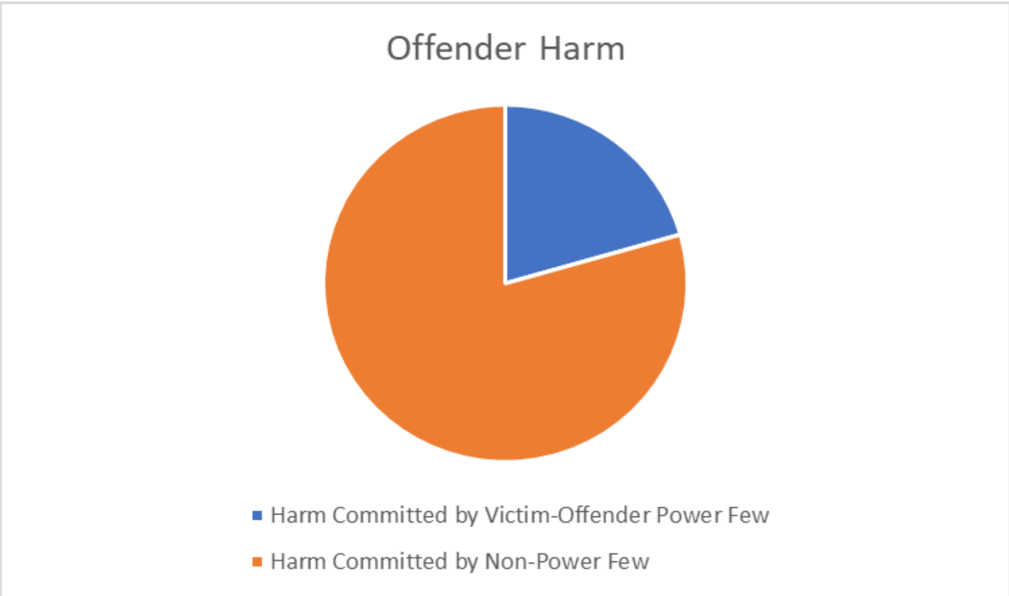
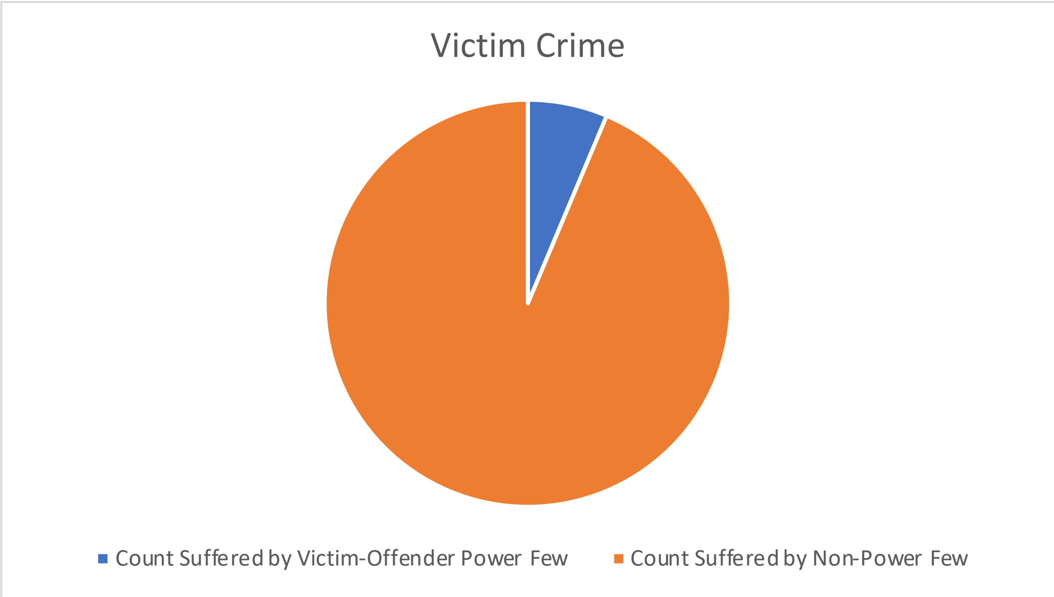


Figure 15. Victim and Offender Harm Suffered/Committed by the Power Few Victim-Offenders

Figure 16 below shows the proportion of crimes these PF Victim-Offenders suffer and commit. This 1.81% suffer 6.34% of crime count and commit 6.35% of crime count.



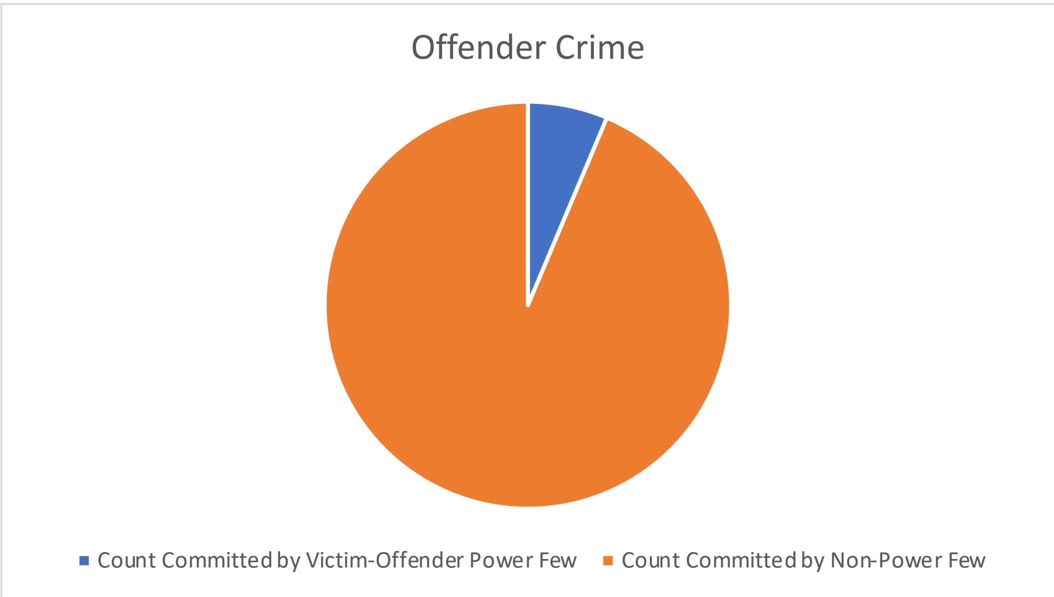


Figure 16. Victim and Offender Crime Suffered/Committed by the Power Few Victim-Offenders

Onset Age for Victim-Offenders

Figure 17 demonstrates the distribution of victims, offenders and victim-offenders based on onset age. It is evident that the onset age of victims is more evenly distributed with a range of between 1.89% and 2.16% first becoming victims every year between the ages of 18 and 36. By comparison the offender onset age peaks at age 18 with 4.15% of offenders. Greater proportions of the offender cohort appear compared to victims at every age between 13 and 39 before the proportions switch. The Victim-Offender pattern of distribution is more closely aligned to that of offenders, with the peak at age 18 compared to victim peaks at ages 19 and 21. The proportion of onset ages for Victim-Offenders are again disproportionately clustered between ages 15-29 with a range between 2.78% and 3.52% per year and only fall below victim proportions at age 40.

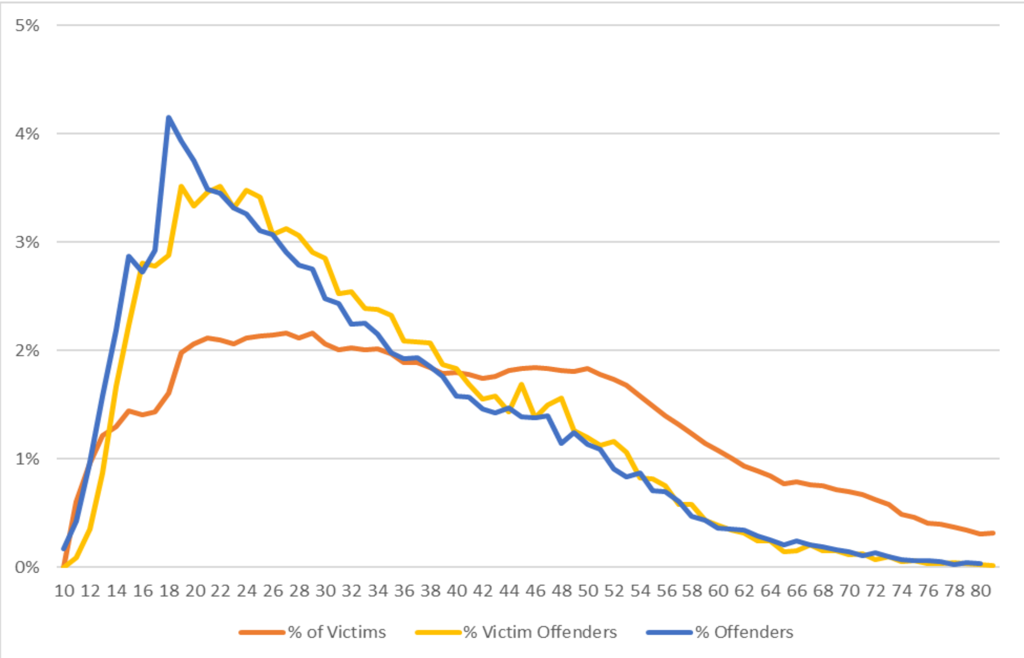


Figure 17. Distribution of Victim, Offender and Victim-Offender Onset by Age

5. Discussion

This research set out to identify concentrations and patterns in the distribution of crime and harm and analyse the predictive accuracy of targeting future victims. Crime can have substantial harmful consequences for victims and so steps to prevent harm have an ethical basis to implementing a repeat victim policy. This chapter focuses on the theoretical, policy and research implications before addressing the limitations of the research.

The research supports and builds upon relevant theory and empirical evidence using a descriptive methodology that employs measures of central tendency to articulate the results by identifying the central or mid-point (Hinton 2004). The analysis could be streamlined and partially automated by exploiting the capabilities of systems such as Business Objects, Excel or SPSS. The descriptive nature and low cost of this research make replication and operationalisation achievable. The strategic implications are that a two-pronged policy could be devised to target (a) named PF individuals; to prevent and reduce future *harm* based on annual analysis, and (b) target repeat victims with a tiered response to limit repeat *crime*. This two-pronged approach enables senior leaders to scale the response up and down based on the concentrations of harm targeted and tolerance for false positives and false negatives similar to Kent Police's Evidence-Based Investigative Tool (E-BIT) (McFadzien et al. 2020, p.13). This would complement experimenting with *tested* practices before upscaling the approach to the wider force (Sherman 2007; Sherman et al. 2014).

The level of impact these findings have varies, they do not provide a panacea for harm reduction and the prediction rate of the highest-harmed victims sits at just below 40%. That said, the harm that could be prevented across this cohort compared to the 'average' victim and the mitigation it could provide for repeat victimisation offers a better alternative to the 'Three R's' style of policing (Sherman 2013). Equally, forecasting high-harm victims in this way would support the force's strategy of providing a first-class service and putting victims and witnesses first; this therefore sits higher on the Policy Hierarchy Scale (Wilcox and Hirschfield 2007). Importantly, opportunities exist to seek to improve the predictive accuracy of targeting victims.

5.1. Theoretical Implications

Predictability

Survival analysis has shown that predicting the PF is challenging. Membership in the PF in one year is not a good predictor of membership in the PF in the subsequent year with less than 8% remaining in the PF (harm) cohorts (Table 17); broadly providing evidence of White's research (2018). This research goes further and illustrates that attrition from the PF continues after the second year with a maximum of 2.31% remaining; showing similar but less severe decay as has been evidenced for offenders (Liggins 2017). The survival analysis is slightly higher for count with 'bi-annual' concentrations showing the greatest survival rates with 16.31% of the PF surviving into the third consecutive time-unit.

When considering different units of time for harm, year-on-year comparison consistently provided the greatest rate of survival (Table 17). 'Years' being the most reliable measure of time for accurate prediction has an important theoretical and policy implication in terms of when analysis should be undertaken to identify targets. Conducting annual analysis of the top 100 victims by both harm and count, as well as by offence type all demonstrated similar rates of attrition from the PF. There was variance between offence types with no victim remaining in the PF for robbery and the greatest survival being 4.88% of victims remaining from years one to two in the PF (harm) and 10.14% for violence without injury remaining in the PF (Count) (Table 20).

In addition to high false-positive rates, feasibility would be an issue. Dudfield (2017) established that over a thousand victims cumulatively suffered over 85% harm and White (2018) found that 13,656 victims suffered 92% harm. These annual volumes are not practical for targeting and so analysis was conducted on the annual PF that made up 10% of total harm (250 victims) and was replicated for count (2276 victims). This analysis explored whether the PF were still important victims to target based on subsequent victimisation regardless of whether they remained in the PF. This analysis found a positive prediction rate of 39.6% for harm and 47.67% for count (Figures 6,7 & 8). Comparatively the count PF was comprised of far more victims making targeting infeasible and they had a crime ratio against the NPF of 2:1 (Table 23). By contrast, the PF harm cohort suffered a harm ratio against the NPF of 11:1 and with 250 victims a year to target; less than 20 per policing district in Kent; this would be feasible. Under this analysis, the rate of survival after the second year then decays further, with both a research and policy implication being that the PF suffering 10% of harm should be targeted, and the analysis repeated annually.

5.2. Policy Implications

Power Few

A replication of Dudfield's (2017) finding that there are a Power Few suffering disproportionately high harm was established. This provides external validity to the concept and evidences its generalisability across regions, with a strength being that it is a population-level study over six years (Ruane 2005; Bachman and Schutt 2017). A consistent annual concentration of 10% total harm between 0.23% and 0.38% of victims, suffering a harm ratio of 29:1 compared to a NPF victims. PF victims also suffered 50% and 80% of harm (Figure 2), which is consistent with the literature in this area (Rima et al. 2019; Bland and Ariel 2015). These distributions are not as concentrated as Dudfield (2017) or White (2018), however there may be confounding effects such as Crime Data Integrity against crime recording standards. PF concentrations were found across different units of time with years and bi-annuals having concentrations of PF victims with the greatest harm ratio to the NPF (Appendix D; Table 12). The distribution of crimes by count follows an initial pattern of concentration before a linear distribution as victims suffer only one offence. The distribution showed that annual patterns showed the greatest disparity between the PF and NPF, however with far less disparity than compared to harm (Figure 3).

The research suggests harm offers the optimal measure of crime to target. The PF (10% harm) cohort is composed of approximately 250 victims, substantially less than count, demonstrating that harm is more concentrated than count among the PF (Tables 11&14). The combination of these analyses demonstrates that harm is distributed in greater concentrations at a smaller number of people. That said, identifying them before they suffer the most harmful event remains a challenge in need of further research. Secondly, the greater disproportionality in harm between the PF and NPF compared to count is indicative of the potential effect that could be gained from targeting those concentrations with *tested* practices to optimise cost-benefit. Similarly, resource allocation for targeting the PF (count) may not be proportionate if the victimisations are in fact low harm.

The survival rates of the PF who go on to suffer repeat victimisation illustrates that whilst 40% may not seem a particularly high survival rate, the elevated harm these victims suffer suggest the overall harm reductions could make targeting a cost-effective policy. The false-negative rate is high; however, this is set against a current lack of formal prediction and associated intervention and so provides a better approach than current practice.

Concern about focussing disproportionately on a PF has been critiqued as this compromises the principle of universality; that a consistent police response should be applied to every victim (Gladwell 2006). The counterargument presented by Sherman (2007) is that ethically, fairness to the victim, impact on the individuals, and achieving maximum harm reduction all justify the position. The 'emotional framing' employed by Gladwell to imply some people lose out can be misleading and instead the concept centres on reducing the most harm through *tested* practices (Kahneman 2011; Sherman 2007).

Escalation and Versatility

This research considered whether escalation in harm was common amongst the PF and whether it was supportive of prediction; neither are the case. Incidences of escalation occur almost equally with de-escalation and repeat escalation is rare with the proportion of PF victims suffering two consecutive escalations being just 3.92% (Tables 24&23). No PF victims suffer five escalations and with repeat escalation declining considerably with each repeat, prediction is limited (Table 25). These findings are consistent with wider research on the subject (Bland and Ariel 2015; 2020). That said, the methodology took a purist approach to escalation so that any de-escalation, regardless of harm score, stopped that individual series of escalation. Different methodologies could be applied, for example by setting benchmarks so that only escalation and de-escalation over a certain harm score is factored in.

When considering versatility, this research has found victim-types seen in previous research and has shown that when considering harm, 'one-timers' represent 35% of the PF, meaning one third of the PF cannot be predicted (Figure 4) (Liggins 2017; Bland and Ariel 2020). Similarly, whilst there are some offence categories such as 'violence' where there are greater proportions of 'specialist' victims; namely 19.21% (Figure 4), 'generalists' suffer greater proportions of crimes across all categories for both the PF (harm) and PF (count) (Figure 5). This section highlights less policy implications for prediction and more for how these data would be employed to direct tested practices as part of a Triple-T strategy (Sherman 2013).

Victim-Offenders

Those individuals that are both PF victims and PF offenders are relatively small in number at 2079 (0.51%) over six years but account for a staggeringly disproportionate volume of harm; suffering 4.82% of victim harm and committing 20.58% of offender harm (Figure 15). This is consistent with concentrations identified in previous research, except covers all crime (Bailey et al. 2020). The attributable harm to the PF Count is less severe with the Victim-Offender PF suffering 6.34% and committing 6.35% of crime. Furthermore, the VOO onset age follows the offender-crime curve with a peak age of 18 (Figure 16). This latter finding answers the questions raised by Jennings et al. (2012) as to when in an individual's life-course the VOO occurs.

This area of the research is limited and would benefit from survival analysis; however, policy implications remain. Firstly, as identified by others, units dealing with offenders such as Offender Management Units should include high-harm offenders' victimisations in their reviews and management of the individual (Sandall et al. 2018). Secondly, the VOO onset age, coupled with the PF victims' proportionate age identified above, presents an opportunity for targeting by Schools' Officers to engage with young persons and intervene with tested practices. Educating officers around these findings and the supporting theory could help them pre-empt and reduce harm, for example research has shown that victim anger features highly in victim responses to crime, which links to retaliation and the dynamic causal perspective (Ditton et al. 1999; Ousey et al. 2010).

Repeat Victimisation

In addition to specific named victims, there are opportunities to inform a repeat victim policy for the wider victim population. One of the purposes of quantitative research is to operationalise and measure certain datasets through the variables; this can derive key 'triggers' to support targeting (Hagan 2014). One of these triggers has already been identified above; the point of overlap between victimisation and offending and the greater attributable mean harm.

Repeat victimisation itself has some predictable patterns as identified in the literature review. In 2019, 23.75% of victims were repeat victims, suffering 44.69% of the crime (Appendix E). Importantly, conditional probability shows that after a third repeat, a victim is more likely than not to suffer a fourth, with a 53.5% probability (Figure 9). This increasing probability over time is consistent with the literature and has important policy implications. Firstly, this data enables a tiered policing response based on the number of victimisations an individual had suffered. This approach was adopted to good effect for burglary victims based on a cocooning strategy in Huddersfield; preventing repeat offences by 'stepping up' the intervention response incrementally after each victimisation (Anderson and Pease 1997). This proportionate response could increase from crime prevention advice to referrals to support mechanisms, to having alarms installed and so on. Secondly, the use of 'flags' to record the number of victimisations a victim has suffered over a rolling year on the force's record management system would alert officers that greater intervention may be needed; something advocated by others (Pease 1998).

Another important finding is the increasing frequency of each repeat victimisations. This collapsing timeframe builds on the literature by evidencing the increased frequency of repeats across all crime types (Polvi et al. 1991; Pease et al. 2018). The point that victims suffer repeats with decreasing intermittency is important in supporting prediction and directing a subsequent policing response (Figure 10). Over 50% of fourth repeats occur in 55 days, meaning targeting needs to prompt and dynamic. Another important finding is that 5.3% of victims suffered same-day victimisations. Further analysis to incorporate the specific time of the offence would enable the exploration of clustered offences as well as peak times for victimisation; something that this research is limited in respect of.

Implementation

A key finding throughout each section is the importance of analysing harm as it identifies previously unseen distributions in the data, supporting the original theoretical standpoint (Sherman et al. 2016; Dudfield 2017; Hiltz et al. 2020). It has been identified that high-harm is concentrated on a smaller number of individuals than high-counts and targeting high crime-counts focuses more on demand management than harm prevention. Crime count still offers several advantages, namely it can show increasing frequency, which is pertinent when considering cases like Fiona Pilkington as it helps identify 'chronic' victims (College of Policing 20.01.2020; Liggins 2017). Using measures of harm and count allows victim typologies to be developed, which in turn could give a more detailed descriptive analysis of a force's victim profile (Weinborn et al. 2017).

A wider policy implication of these issues for operationalising this research is the prudence of conducting a pre-mortem; taking an 'outside view' beyond just the information to hand in order to avert failure through the 'planning fallacy' of working towards the 'best-case scenario' (Kahneman 2011). Operationalising this research with a clear implementation strategy would be a worthy investment of time and would be achievable given the force's innovative culture. By adopting a detailed implementation framework to develop analytical capability in light of the above, including the training of staff, determining the resource requirement and securing stakeholder buy-in from partners to support targeted victims, this research could be operationalised (Fixsen et al. 2005; Meyers et al. 2012). As identified within the above sections, training staff in the importance of the aspects identified so that they recognise them and respond accordingly based on tested practices is essential.

5.3. Research Implications

Demographics

The above results are based on univariate survival analysis working solely on prior victimisation. Results from analysis of demographic variables illustrated a statistical difference between females and males in the PF Harm (10%) cohort. Females suffered 78.13% of the harm suffered with a mean harm score compared to males of 1.4:1 (Figure 11 and Table 28). Similarly for count, females suffered more victimisations but to a lesser extent than harm (Figure 12). In the PF (harm) cohort, a greater proportion of victims were younger compared to the other PF cohorts with a peak at age 16 following an initial rise at age 12 (Figure 13). Similarly, other than the outliers aged in their 80's, the highest mean harm scores were found in the PF Harm (10%) cohort in the age bracket 10-19-years old (Table 28). For count, the highest mean count scores are found later in life. These findings support previous studies and advocate further multivariate analysis overlaying prior victimisation with socio-demographic variables either as descriptive analysis or as a random forests model such as those used in Durham's HART model to try and improve forecasting prediction (Roberts 2008; Oswald et al. 2018). Linked to this proposed research would be incorporating the VOO as a variable, as well as crime types and categories such as domestic abuse.

Data Quality

During the data extraction and initial analysis, it was identified that data quality was an issue. Demographics were found to often be under-recorded (Table 8) and whilst there were numerous 'flags' available for use, initial scrutiny identified that these may not be reliably applied. One implication is the impact of non-mandatory demographic fields within a force's record management system. This is particularly pertinent given the current climate, focus on policing, engagement with minority communities, police responses and a potential threat to police legitimacy (Sherman 2021).

5.4. Limitations

5.4.1. Confounding Effects

This study does not seek to explain cause and effect and is purely descriptive, which in itself limits any understanding to *what* harm is occurring and to *whom*, as opposed to *why*. In addition, certain confounding effects have not been controlled which may be relevant to the patterns within the data. The main examples of this would include 'External Events' such as new laws or policy amendments, for example greater rigour in identifying stalking, or the Modern Slavery Act 2015 which came into force during this period of data (Bachman and Schutt 2017). Another example would include 'Endogenous Change' including Regression to the Mean, for example, when describing harm escalation, an extreme crime may lead to a description of subsequent de-escalating harm, even though subsequent harm scores actually remain high (Bachman and Schutt 2017).

5.4.2. Crime Data Integrity

As highlighted in the methodology, the force's Crime Data Integrity has fluctuated over the six years, with improvements correlating to an increase in recorded crime, leaving a question of whether crime has *actually* increased. Table 30 illustrates the increase/decrease in crime year-on-year. Partway through 2017 was when Kent Police began remedial action to address poor Crime Data Integrity with that year seeing the highest increase in crime. The issue is that purposeful adjustments in data collection procedures during the measurement period can create issues, for example victims may show as suffering more crime, when this is just a product of crime recording (Hatry and Newcomer 2015).

Table 30. Recorded Crime Increase/Decrease Year-on-Year

Year	Number of Crimes Recorded	Percentage Increase/Decrease on Previous Year
2014	111,149	NA
2015	112,990	1.66%
2016	127,449	12.80%
2017	166,711	30.80%
2018	194,660	16.76%
2019	186,697	-4.09%

5.4.3. Under-reporting

Under-reporting has been identified as an issue within police records especially when compared to the Crime Survey of England and Wales (Maguire and McVie 2017). Non-reporting can occur for many reasons, including victims not wanting to waste theirs or the police's time, fear of embarrassment, or as a result of previous negative experiences with the police (Tarling and Morris 2010; Murphy and Barkworth 2014). Victims of certain crimes may make a cost-benefit assessment, for example in domestic abuse, immediate police protection is offset against fear of later reprisals (Felson et al. 2002). Furthermore, there is evidence that repeat victims are actually less likely to report on the basis that authorities cannot help (van Dijk 2001).

Under-reporting creates a risk to measurement validity on the basis that the data may not represent what it intends, namely, the crime actually suffered by the population of Kent (Ruane 2005). Linked to this are *Hidden Harms*, including child sex offences, Human Trafficking, and Domestic Abuse where fear, language barriers and not identifying as a victim can create barriers to reporting. The police's understanding of this demand has previously been critiqued and it is acknowledged that a more thorough dataset comprising multiple sources would give a better understanding of actual harm (HMICFRS 2018).

6. Conclusion

Repeat harm *can* be predicted, meaning prevention is possible, and based on police records. This research set out to establish whether victimisations could be accurately forecast and therefore prevented.

The research looked at four main areas; whether there were PF victims suffering concentrations of harm and count, and how consistent this was over time; survival analysis of these PF victims over time; patterns in the victimisation data in terms of conditional probability, frequency, escalation and versatility; and the overlap between victims and offenders. As a result of this descriptive analysis, there is now empirical evidence establishing that there are concentrations of harm and PF victims in Kent. In some years, as few as 12.93% of victims suffer 80% harm, 2.94% suffer 50% harm and 0.23% suffer 10% harm; less than 250 victims. The evidence also shows how substantial the difference in harm is between the PF and NPF, with the greatest disparity showing a harm ratio of 47:1. The contrast with crime count is not as severe, showing the value of using the CCHI to measure the harm suffered (Sherman et al. 2016). This approach to understanding and prioritising the protection of victims allows police leaders to maximise effect, namely harm reduction. Similarly, harm is useful more generally, for example, whilst not conducive to prediction, escalation of harm could support officers seeking remands of offenders or Domestic Violence Protection Orders.

The survival analysis is the crux of this research, as patterns in the distribution are best operationalised if they can be forecast. This research provides evidence of the limited cost-effectiveness that would come with targeting certain concentrations. If targeting the PF that suffer 80% of harm, the volumes of victims would not be practical; if targeting count, the degree of harm being prevented is unknown and the limited disparity with NPF victims may make any strategy disproportionate; and if targeting new concentrations month-on-month, the survival rate is so low, the number of true positives to false positives highlights the respective inaccuracy and consequent cost-ineffectiveness. Importantly, the analysis has shown that targeting the PF suffering 10% harm on an annual basis would have a positive prediction value of nearly 40% with a harm ratio of 11:1 to the NPF, with an achievable number of victims to target. As such, it would be recommended that the potential cost-benefit of this approach means it should be operationalised. The difference in harm and count based on gender and age, and the difference in survival analysis by crime type support the recommendation that further research should be undertaken to conduct a multivariate analysis to try and improve the accuracy of prediction.

This research found further evidence to support the point that repeat victimisation generally occurs quickly (Pease 1998) and further found that each repeat, up to the tenth, occurs with greater frequency and shorter intermittency than the last. Similarly, the conditional probability of suffering the next repeat increases with each consecutive victimisation; a victim is more likely than not to suffer a fourth after suffering three repeats. It is recommended that a repeat victim policy based on these findings is developed alongside the targeting of PF concentrations. As part of this, educating the workforce on some of these concepts and making better use of flags could optimise the effect, as could improving data quality. Linked to this, the study has shown the proportions of victims that are 'one-timers', 'specialists' and 'generalists'. Understanding these patterns allows for both differential, and tiered policing responses that can be contextualised for greater effect as achieved in other victim-based experimental research (Grove et al. 2012).

The final area of research centred on the VOO. The concentration of harm attributable to those individuals in the PF of both the victim and offender populations is substantial. These concentrations justify a recommendation that survival analysis is undertaken on this cohort, akin to what has been explored here for victims on the basis of potential cost-benefit. As it is, the disproportionately high-harm attributable to victim-offenders is such that this should be a trigger that response officers and investigating officers should be alert to.

The research question was to determine to what extent the 'power-few' high-harm victims can be predicted based on prior victimisation. Ultimately, for named individuals, 40% of the most harmed victims can be predicted and therefore targeted. This can be coupled by targeting highly victimised individuals through the number of repeats they suffer.

In closing, this research provides the analysis needed to present an evidence-based policing approach to predicting and *targeting* high-harm victims based on prior victimisation. The opportunity to operationalise this research will be explored and additional research as outlined above, considered. To translate this work to both policing and the wider public, the term 'Power Few' will be replaced 'High-Priority Victims' (HPVs); as a neutral term that still signifies the most harmed victims (Sherman 2019). Whilst some aspects of predicting victimisation remain elusive, such as 'one-time' victims, in the words of Graham Farrell (1995), 'there will never exist a perfect means of crime prevention'. What this research does provide, is evidence to improve what we already do.

7. References

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8. Appendices

Appendix A: Outcomes Codes – Coded to identify 'Detected' Crimes with a positive outcome.

Outcome Code	Detected / Undetected
Type 1 - Charged/Summonsed/Postal Requisition	Detected
Type 1A - Charged/Summons - alternate offence. Offender has been charged under the alternate offence rule.	Detected
Type 2 - Caution/Conditional Caution - Youth	Detected
Type 2A - Caution/Conditional Caution - Youth - alternate offence. Offender is a juvenile and has been given a youth caution under the alternate offences rule.	Detected
Type 3 - Caution/Conditional Caution - Adult	Detected
Type 3A - Caution/Conditional Caution - Adult - alternate offence. Offender has been given a simple caution under the alternate offences rule.	Detected
Type 4 - TIC - Taken into Consideration	Detected
Type 6 - Penalty Notice for Disorder	Detected
Type 7 - Cannabis/Khat Warning	Detected
Type 8 - Community Resolution (Crime)	Detected
Type 5 - Offender has died	Undetected
Type 9 - Prosecution Not In the Public Interest (CPS)	Undetected
Type 10 - Formal Action Against Offender is not in the Public Interest (Police)	Undetected
Type 11 - Prosecution Prevented-Named Suspect Identified But Is Below The Age Of Criminal Responsibility	Undetected
Type 12 - Prosecution Prevented-Named Suspect Identified But Is Too Ill (Physical Or Mental Health) To Prosecute	Undetected
Type 13 - Prosecution Prevented-Named Suspect Identified But Victim Or Key Witness Is Dead Or Too Ill To Give Evidence	Undetected
Type 14 - Evidential Difficulties Victim Based- Suspect Not Identified: Crime Confirmed But The Victim Either Declines Or Unable To Support Further Police Investigation To Identify The Offender	Undetected
Type 15 - Named Suspect Identified: Victim Supports Police Action But Evidential Difficulties Prevent Further Action	Undetected
Type 16 - Named Suspect Identified: Evidential Difficulties Prevent Further Action: Victim Does Not Support (Or Has Withdrawn Support From) Police Action	Undetected
Type 17 - Prosecution Time Limit Expired: Suspect Identified But Prosecution Time Limit Has Expired	Undetected
Type 18 - Investigation Complete; No Suspect Identified. Crime Investigated As Far As Reasonably Possible-Case Closed Pending Further Investigative Opportunities Becoming Available	Undetected
Type 20 - Further action resulting from the crime report will be undertaken by another body or agency subject to the victim (or person acting on their behalf) being made aware of the act to be taken	Undetected
Type 21 - Further investigation resulting from crime report which could provide evidence sufficient to support formal action against the suspect is not in the public interest - police decision.	Undetected
Type 22 - Diversionary, educational or intervention activity, resulting from the crime report, has been undertaken and it is not in the public interest to take any further action.	Undetected
Type AF – Action Fraud record filed temporarily awaiting result from master AF investigation	Undetected

Appendix B: Cambridge Crime Harm Index (Sherman et al. 2016) [Edited Version]

HO Code	Home Office Class	Offence description	Cambridge Crime Harm Index Score	Sentence Starting Point	Lowest starting point sentence	HO Class Desc	Crime Tree LV4 Desc	Crime Tree LV3 Desc	Crime Tree LV2 Desc	Crime Tree LV1 Desc
001/01	1	Murder - victim one year of age or older	5475	15 years	None	MURDER	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
002/00	2	Attempt murder - victim aged under 1 year	3285	9 years	6 years	MURDER (ATTEMPT)	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
003/01	03B	Threats to kill	10	Medium level community order	Low level community order	THREATS TO KILL	VIOLENCE WITHOUT INJURY	VIOLENCE WITHOUT INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
004/04	04/04	Cause death by dangerous driving	1095	3 years	2 years	CAUSING DEATH OR SERIOUS INJURY BY DANGEROUS DRIVING	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
004/10	04/10	Corporate Manslaughter	2894	£300,000	£180,000	CORPORATE MANSL-AUGHTER	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
005/01	05D	Assault - S18 - GBH grievous bodily harm with intent	1460	4 years' custody	3 years	ASSAULT W/I CAUSE SERIOUS HARM	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
008/01	08N	Assault - S20 - GBH Grievous bodily harm without intent	18.75	High level community order	Low level community order	ASSAULT WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
008/06	08N	Assault - S47 - AOABH assault occasioning actual bodily harm	10	Medium level community order	Band A fine	ASSAULT WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE WITH INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
008/57	105B	Racially / religiously aggravated common assault	10	Medium level community order	Band A fine	RACIALLY/ RELIGIOUSLY AGG ASSAULT WITHOUT INJURY	VIOLENCE WITHOUT INJURY	VIOLENCE WITHOUT INJURY	VIOLENCE AGAINST THE PERSON	VICTIM BASED
019/08	19C	Sex - Rape a woman 16 years of age or over - SOA 2003	1825	5 years	4 years	RAPE OF FEMALE OVER 16	RAPE	RAPE	SEXUAL OFFENCES	VICTIM BASED
028/03	28AB	Burglary dwelling - With intent to steal	18.75	High level community order	Medium level community order	BURGLARY IN A DWELLING	DOMESTIC BURGLARY	BURGLARY	THEFT OFFENCES	VICTIM BASED
029/00	29	Aggravated burglary - dwelling	365	1 year custody	High level community order	AGGR BURGLARY DWELLING	DOMESTIC BURGLARY	BURGLARY	THEFT OFFENCES	VICTIM BASED
1934/01/02	34B	Robbery - Personal	365	1 year custody	High level community order	ROBBERY OF PERSONAL PROPERTY	ROBBERY OF PERSONAL PROPERTY	ROBBERY OF PERSONAL PROPERTY	ROBBERY	VICTIM BASED
048/01	48	Theft of motor vehicle	5	Low level community order	Band C fine	THEFT OF MOTOR VEHICLE	THEFT OF MOTOR VEHICLE	VEHICLE CRIME	THEFT OFFENCES	VICTIM BASED
053/40/02	53D	Fraud by false representation - Other methods	10	Medium level community order	Band B fine	FRAUD BY FALSE REP OTHER FRAUDS	FRAUD & FORGERY	FRAUD & FORGERY	FRAUD & FORGERY	FRAUD & FORGERY
056/01	56A	Arson with intent to endanger life	2190	6 years custody		ARSON ENDANGERING LIFE	ARSON	ARSON	CRIMINAL DAMAGE & ARSON	VICTIM BASED
058/00/04	58D	Criminal damage other - value over £5000	84	12 weeks custody	6 weeks	CRIMINAL DAMAGE OTHER	CRIMINAL DAMAGE	CRIMINAL DAMAGE	CRIMINAL DAMAGE & ARSON	VICTIM BASED

Appendix C: HMICFRS Crime Tree (HMICFRS 2017b)

	Crime Tree Level 1	Crime Tree Level 2	Crime Tree Level 3	Crime Tree Level 4
Crime	Victim-Based Crime	Violence Against the Person	Homicide	
			Violence With Injury	
			Violence Without Injury	
		Sexual Offences	Rape	
			Other Sexual Offences	
		Robbery	Robbery of Business Property	
			Robbery of Personal Property	
		Theft Offences	Burglary	Burglary in a Dwelling
				Burglary in a Building Other Than a Dwelling
			Vehicle Offences	
			Theft from the Person	
			Bicycle Theft	
			Shoplifting	
			All Other Theft Offences	
		Criminal Damage and Arson Offences	Criminal Damage	
			Arson	
	Other Crimes Against Society	Drug Offences	Trafficking of Drugs	
			Possession of Drugs	
		Possession of Offensive Weapons		
		Public Order Offences		
		Miscellaneous Crimes Against Society		

Appendix D: Power Few Distributions with Harm Scores and Harm Ratios by Units of Time

Unit of Time	Period of Time	% Cumulative Harm (PF Threshold)	Cumulative Harm Score at Threshold	% of Victim Population (PF)	Number of Victims in PF	PF Mean Harm Score	NPF Mean Harm Score	PF vs NPF Harm Ratio
Years	2014	80%	6260090	15.15%	9981	627.2	28.0	22.4:1
		10%	783955	0.38%	250	3135.8	107.3	29.2:1
	2015	80%	6995668	13.61%	9169	763.0	30.1	25.4:1
		10%	874653	0.37%	247	3541.1	117.3	30.2:1
	2016	80%	8277816	12.93%	9822	842.8	31.3	26.9:1
		10%	1037116	0.30%	226	4589.0	123.0	37.3:1
	2017	80%	11274660	13.50%	12708	887.2	34.6	25.6:1
		10%	1409543	0.26%	248	5683.6	135.1	42.1:1
	2018	80%	13017101	13.26%	13508	963.7	36.9	26.2:1
		10%	1627492	0.23%	238	6838.2	144.1	47.4:1
	2019	80%	12516628	13.26%	13274	942.9	36.0	26.2:1
		10%	1566145	0.28%	283	5534.1	141.0	39.2:1
Bi-Annuals	B1 2017	80%	5419180	12.91%	6139	882.7	32.7	27:1
		10%	677398	0.29%	139	4873.4	128.6	37.9:1
	B2 2017	80%	5856083	13.15%	7170	816.7	30.9	26.4:1
		10%	732010	0.29%	159	4603.8	121.2	38:1
	B1 2018	80%	6347711	12.54%	6838	928.3	33.3	27.9:1
		10%	793464	0.23%	125	6347.7	131.2	48.4:1
	B2 2018	80%	6670149	13.09%	7432	897.5	33.8	26.6:1
		10%	833769	0.28%	159	5243.8	132.5	39.6:1
	B1 2019	80%	6145991	12.92%	6937	886.0	32.9	27:1
		10%	768249	0.30%	163	4713.2	129.1	36.5:1
	B2 2019	80%	6371349	12.80%	7056	903.0	33.1	27.3:1
		10%	796419	0.30%	168	4740.6	130.4	36.4:1
Quarters	Q3 2018	80%	3446278	12.16%	3832	899.3	31.1	28.9:1
		10%	430785	0.28%	87	4951.5	123.4	40.1:1
	Q4 2018	80%	3223871	13.36%	3904	825.8	31.8	26:1
		10%	402984	0.32%	94	4287.1	124.5	34.4:1
	Q1 2019	80%	3020613	12.89%	3625	833.3	30.8	27:1
		10%	377577	0.29%	82	4604.6	121.2	38:1
	Q2 2019	80%	3125378	12.19%	3555	879.1	30.5	28.8:1
		10%	390672	0.34%	100	3906.7	121.0	32.3:1
	Q3 2019	80%	3310380	12.07%	3638	909.9	31.2	29.2:1
		10%	413798	0.31%	93	4449.4	123.9	35.9:1
	Q4 2019	80%	3060969	12.90%	3697	828.0	30.7	27:1
		10%	382621	0.34%	97	3944.5	120.6	32.7:1
Months	M7 2019	80%	1163070	12.25%	1398	832.0	29.0	28.6:1
		10%	145384	0.33%	38	3825.9	115.1	33.2:1
	M8 2019	80%	1144933	11.55%	1223	936.2	30.6	30.6:1
		10%	143117	0.28%	30	4770.6	122.0	39.1:1
	M9 2019	80%	1002377	11.98%	1252	800.6	27.2	29.4:1
		10%	125297	0.34%	36	3480.5	108.3	32.1:1
	M10 2019	80%	1049780	12.48%	1334	786.9	28.1	28:1
		10%	131223	0.33%	35	3749.2	110.9	33.8:1
	M11 2019	80%	1021399	12.78%	1318	775.0	28.4	27.3:1
		10%	127675	0.37%	38	3359.9	111.8	30:1
	M12 2019	80%	989790	12.25%	1178	840.2	29.3	28.7:1
		10%	123724	0.37%	36	3436.8	116.2	29.6:1

Appendix E: Number of Repeat Victims and Offences 2014-2019

Year	Percentage of Victims that were Repeats	Percentage of Offences Suffered by Repeat Vicitms
2014	11.89%	24.68%
2015	13.15%	27.56%
2016	45.39%	32.04%
2017	25.54%	39.46%
2018	22.38%	46.63%
2019	23.75%	44.69%

Appendix F: Power Few Distributions with Crime Counts and Count Ratios by Units of Time

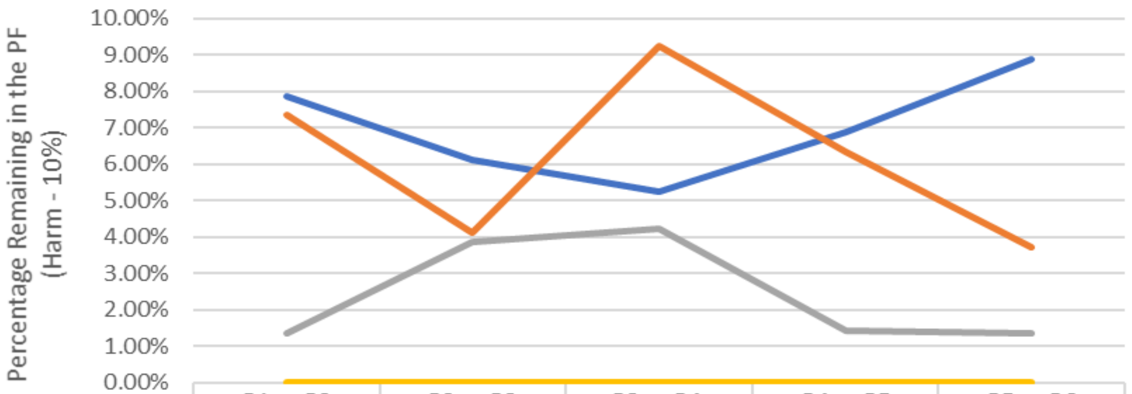
Unit of Time	Period of Time	% Cumulative Count or Repeat Victimisation (PF Threshold)	Cumulative Count at Threshold (& % of Total)	% of Victim Population (PF)	Number of Victims in PF	PF Mean Count of Victimisations	NPF Mean Count of Victimisations	PF vs NPF Count Ratio
Years	2014	Repeat	19891 (24.68%)	11.89%	8192	2.4	1	2.4:1
	2015	Repeat	23050 (27.56%)	13.15%	9175	2.5	1	2.5:1
	2016	Repeat	31159 (32.04%)	15.20%	11841	2.6	1	2.6:1
	2017	Repeat	50299 (39.46%)	18.83%	17899	2.8	1	2.8:1
	2018	Repeat	68813 (46.63%)	22.38%	22706	3.0	1	3:1
	2019	Repeat	62993 (44.69%)	21.23%	21012	3.0	1	3:1
Bi-Annuals	B1 2017	Repeat	16533 (28.72%)	13.67%	6497	2.5	1	2.5:1
	B2 2017	Repeat	22588 (32.93%)	15.64%	8527	2.6	1	2.6:1
	B1 2018	Repeat	28260 (38.93%)	18.72%	10211	2.8	1	2.8:1
	B2 2018	Repeat	31393 (40.79%)	19.73%	11201	2.8	1	2.8:1
	B1 2019	Repeat	27542 (38.66%)	18.62%	10003	2.8	1	2.8:1
	B2 2019	Repeat	27628 (37.98%)	18.17%	10018	2.8	1	2.8:1
Quarters	Q3 2018	Repeat	14227 (35.28%)	17.18%	5414	2.6	1	2.6:1
	Q4 2018	Repeat	12125 (33.09%)	16.12%	4712	2.6	1	2.6:1
	Q1 2019	Repeat	11124 (31.86%)	15.43%	4341	2.6	1	2.6:1
	Q2 2019	Repeat	11764 (32.37%)	15.76%	4597	2.6	1	2.6:1
	Q3 2019	Repeat	12365 (32.72%)	15.69%	4732	2.6	1	2.6:1
	Q4 2019	Repeat	10527 (30.11%)	14.71%	4214	2.5	1	2.5:1
Months	M7 2019	Repeat	3204 (24.17%)	11.88%	1355	2.4	1	2.4:1
	M8 2019	Repeat	3109 (25.06%)	12.15%	1286	2.4	1	2.4:1
	M9 2019	Repeat	2875 (23.72%)	11.52%	1204	2.4	1	2.4:1
	M10 2019	Repeat	2705 (22.15%)	11.02%	1178	2.3	1	2.3:1
	M11 2019	Repeat	2633 (22.3%)	11.02%	1137	2.3	1	2.3:1
	M12 2019	Repeat	2352 (21.5%)	10.67%	1026	2.3	1	2.3:1

Appendix G: Survival Rates of the Power Few for harm and count by Units of Time

			Time Period											
			P1		P2		P3		P4		P5		P6	
	PF Threshold	Unit of Time	No. of Victims	% of Victims	No. of Victims	% of Victims	No. of Victims	% of Victims	No. of Victims	% of Victims	No. of Victims	% of Victims	No. of Victims	% of Victims
Harm	10%	Years	216	100.00%	17	7.87%	10	4.63%	5	2.31%	7	3.24%	6	2.78%
		BiAnnuals	136	100.00%	10	7.35%	8	5.88%	3	2.21%	1	0.74%	4	2.94%
		Quarters	75	100.00%	1	1.33%	3	4.00%	1	1.33%	0	0.00%	3	4.00%
		Months	36	100.00%	0	0.00%	1	2.78%	0	0.00%	0	0.00%	0	0.00%
	80%	Years	9456	100.00%	638	6.75%	485	5.13%	462	4.89%	437	4.62%	398	4.21%
		BiAnnuals	2798	100.00%	266	9.51%	213	7.61%	192	6.86%	165	5.90%	147	5.25%
		Quarters	3831	100.00%	176	4.59%	138	3.60%	122	3.18%	96	2.51%	99	2.58%
		Months	1393	100.00%	29	2.08%	31	2.23%	34	2.44%	23	1.65%	16	1.15%
Count	Repeat Victims	Years	1884	100%	554	29.41%	435	23.09%	451	23.94%	475	25.21%	409	21.71%
		BiAnnuals	1876	100%	641	34.17%	520	27.72%	451	24.04%	371	19.78%	346	18.44%
		Quarters	1729	100%	407	23.54%	298	17.24%	273	15.79%	248	14.34%	188	10.87%
		Months	304	100%	52	17.11%	36	11.84%	26	8.55%	19	6.25%	17	5.59%

Appendix H: Consistency of the PF Survival by Units of Time Replicated Across Time Periods

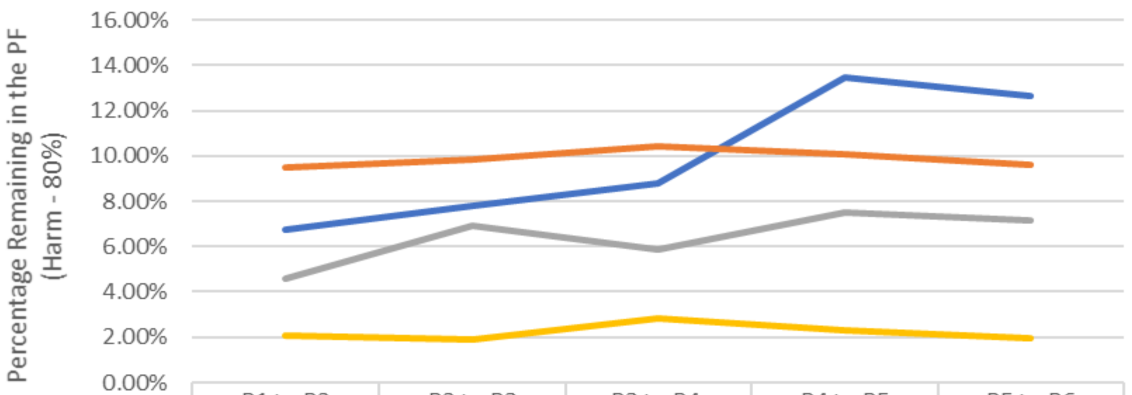
Harm – PF (10% Harm)



	P1 to P2	P2 to P3	P3 to P4	P4 to P5	P5 to P6
Year	7.87%	6.10%	5.24%	6.88%	8.86%
BiAnnual	7.35%	4.11%	9.24%	6.33%	3.70%
Quarterly	1.33%	3.85%	4.23%	1.43%	1.33%
Monthly	0.00%	0.00%	0.00%	0.00%	0.00%

Period of Time

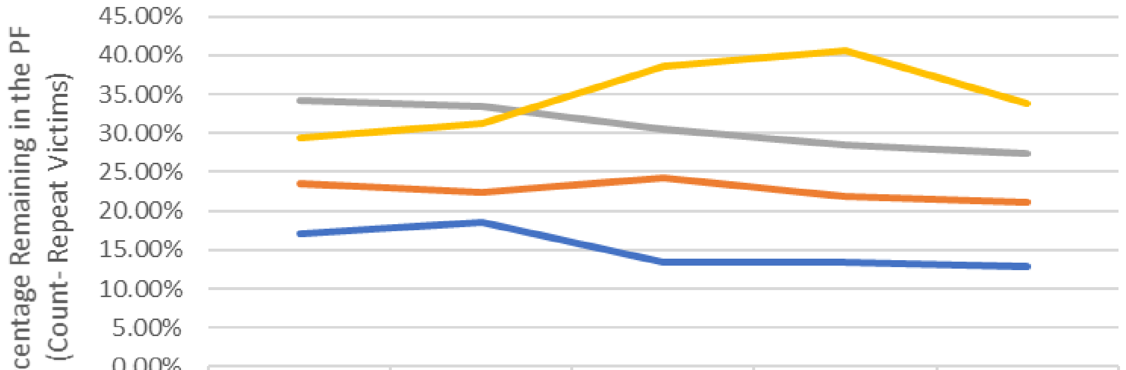
Harm – PF (80% Harm)



	P1 to P2	P2 to P3	P3 to P4	P4 to P5	P5 to P6
Year	6.75%	7.82%	8.79%	13.48%	12.65%
BiAnnual	9.51%	9.87%	10.43%	10.06%	9.60%
Quarterly	4.59%	6.92%	5.85%	7.50%	7.16%
Monthly	2.07%	1.87%	2.83%	2.28%	1.95%

Period of Time

Count – PF (Repeat Victimisation)



	P1 to P2	P2 to P3	P3 to P4	P4 to P5	P5 to P6
Monthly	17.11%	18.56%	13.38%	13.42%	12.86%
Quarterly	23.54%	22.42%	24.21%	21.83%	21.13%
BiAnnual	34.17%	33.51%	30.58%	28.43%	27.41%
Year	29.41%	31.18%	38.55%	40.69%	33.75%

Appendix I: Power to Victim Cohort (Harm and Count) Survival Over Time with Mean Harm Scores / Counts and Harm Ratios

	Power Few Threshold	Year	Number of Victims in Cohort	% of Victim Population	Cohort Mean Harm Score	Victim Population Mean Harm Score	Harm Ratio (Cohort to Victim Population)
Harm	10% Total Harm	2014	250	0.38%	3135.82 (SD=1797.8)	118.8 (SD=359.2)	26.4:1
		2015	99	0.15%	1357.78 (SD=3127.32)	129.9 (SD=404.2)	10.5:1
		2016	56	0.07%	1546.59 (SD=3042.84)	136.26 (SD=448.2)	11.4:1
		2017	41	0.04%	1861.18 (SD=2912.09)	149.75 (SD=494.06)	12.4:1
		2018	31	0.03%	1791.87 (SD=2673.72)	159.77 (SD=563.17)	11.2:1
		2019	23	0.02%	1742.59 (SD=2569.57)	156.28 (SD=517.06)	11.2:1
	80% Total Harm	2014	9981	15.15%	627.2 (SD=725.07)	118.8 (SD=359.2)	5.3:1
		2015	2081	3.09%	358.91 (SD=952.97)	129.9 (SD=404.2)	2.8:1
		2016	940	1.24%	480.39 (SD=1128.52)	136.26 (SD=448.2)	3.5:1
		2017	582	0.62%	626.48 (SD=1383.51)	149.75 (SD=494.06)	4.2:1
		2018	401	0.39%	691.97 (SD=1413.58)	159.77 (SD=563.17)	4.3:1
		2019	285	0.28%	610.82 (SD=1250.68)	156.28 (SD=517.06)	3.9:1
					Cohort Mean Count of Victimisations	Victim Population Mean Count of Victimisations	Count Ratio (Cohort to Victim Population)
Count	10% Total Count of Victimisations	2014	2276	3.30%	3.54 (SD=1.67)	1.17 (SD=0.6)	3:1
		2015	1085	1.56%	2.43 (SD=2.9)	1.19 (SD=0.7)	2:1
		2016	611	0.78%	3.03 (SD=5.02)	1.25 (SD=0.88)	2.4:1
		2017	407	0.43%	9.4 (SD=4.47)	1.18 (SD=1.34)	8:1
		2018	306	0.30%	6.12 (SD=21.97)	1.45 (SD=1.8)	4.2:1
		2019	227	0.23%	5.43 (SD=12.17)	1.42 (SD=1.4)	3.8:1
	Repeat Victims	2014	8192	11.89%	2.43 (SD=1.12)	1.17 (SD=0.6)	2.1:1
		2015	2890	4.14%	1.99 (SD=2.09)	1.19 (SD=0.7)	1.7:1
		2016	1452	1.86%	2.55 (SD=3.62)	1.25 (SD=0.88)	2:1
		2017	920	0.97%	3.64 (SD=6.77)	1.18 (SD=1.34)	3.1:1
		2018	652	0.64%	4.91 (SD=15.36)	1.45 (SD=1.8)	3.4:1
		2019	452	0.46%	4.55 (SD=9.12)	1.42 (SD=1.4)	3.2:1

Appendix J: Frequency of Re-Victimisation by Repeat Number

	Repeat Number									
Revictimisation Day	1	2	3	4	5	6	7	8	9	10
1	1.53%	1.99%	2.32%	3.02%	3.01%	4.24%	3.55%	4.24%	5.30%	5.50%
2	2.63%	3.50%	4.44%	5.30%	5.71%	7.47%	6.19%	6.51%	8.61%	10.68%
3	3.52%	4.72%	5.85%	7.07%	7.95%	9.30%	9.13%	8.77%	12.36%	14.89%
4	4.25%	5.78%	7.13%	8.97%	9.49%	11.39%	11.26%	10.44%	15.45%	19.42%
5	4.91%	7.03%	8.46%	10.31%	11.19%	13.42%	13.59%	13.16%	18.54%	21.36%
6	5.62%	7.89%	9.70%	11.94%	12.81%	15.13%	15.52%	14.52%	20.09%	25.57%
7	6.31%	8.75%	11.04%	13.67%	15.09%	16.65%	17.55%	16.34%	21.85%	27.51%
8	6.90%	9.67%	12.15%	15.05%	16.29%	18.16%	19.98%	18.76%	22.96%	28.48%
9	7.40%	10.49%	13.13%	16.26%	17.83%	19.75%	22.11%	21.63%	24.94%	31.39%
10	7.88%	11.42%	14.21%	17.47%	19.22%	21.01%	23.33%	22.69%	27.37%	33.98%
11	8.34%	12.29%	15.15%	18.47%	20.57%	22.22%	24.85%	24.66%	28.92%	34.30%
12	8.88%	12.90%	16.03%	19.68%	21.69%	23.80%	26.88%	26.17%	30.24%	35.60%
13	9.35%	13.59%	16.97%	20.76%	23.20%	25.82%	28.09%	29.20%	31.35%	37.86%
14	9.82%	14.31%	17.76%	21.70%	24.70%	27.09%	29.72%	30.71%	32.45%	39.48%
15	10.24%	15.13%	18.64%	22.79%	26.05%	28.04%	30.83%	32.83%	33.77%	40.78%
16	10.69%	15.80%	19.32%	23.71%	27.02%	29.18%	31.74%	33.89%	34.88%	41.42%
17	11.10%	16.40%	20.09%	24.71%	27.94%	30.70%	33.27%	36.46%	36.64%	43.69%
18	11.59%	17.09%	20.89%	25.77%	29.29%	31.52%	34.28%	38.12%	37.31%	45.63%
19	12.02%	17.82%	21.63%	26.57%	30.22%	32.59%	35.70%	39.94%	39.51%	46.60%
20	12.40%	18.47%	22.55%	27.47%	31.15%	33.48%	36.82%	41.15%	40.40%	47.57%
21	12.85%	19.16%	23.33%	28.49%	32.30%	34.11%	37.73%	42.36%	41.50%	49.84%
22	13.28%	19.70%	24.19%	29.55%	33.46%	35.00%	38.74%	43.42%	43.71%	50.49%
23	13.66%	20.32%	24.93%	30.37%	34.50%	36.08%	39.66%	44.48%	44.81%	52.10%
24	13.99%	20.88%	25.63%	31.29%	35.24%	37.15%	40.06%	45.39%	47.24%	53.07%
25	14.40%	21.44%	26.50%	31.98%	36.01%	38.42%	41.48%	46.44%	48.34%	53.72%
26	14.76%	21.93%	27.27%	32.61%	37.13%	39.11%	42.29%	47.50%	49.45%	54.69%
27	15.14%	22.35%	27.74%	33.42%	37.78%	40.38%	43.10%	48.56%	50.55%	55.66%
28	15.54%	22.96%	28.31%	34.18%	38.67%	41.52%	44.42%	49.77%	51.66%	55.99%
29	15.92%	23.49%	28.98%	34.82%	39.48%	42.72%	45.74%	50.98%	52.76%	56.96%
30	16.24%	24.10%	29.71%	35.88%	40.33%	43.73%	46.86%	51.29%	53.64%	58.25%
31	16.61%	24.60%	30.25%	36.59%	41.07%	44.62%	47.67%	52.19%	53.86%	58.90%
32	16.95%	25.04%	30.88%	37.51%	41.72%	45.32%	48.38%	52.80%	54.53%	60.52%
33	17.27%	25.52%	31.49%	38.31%	42.65%	45.95%	49.09%	53.25%	56.29%	61.81%
34	17.64%	26.05%	32.22%	38.87%	43.19%	46.58%	49.80%	54.46%	57.84%	62.14%
35	17.97%	26.61%	32.94%	39.61%	43.73%	47.34%	50.41%	55.67%	58.28%	62.78%
36	18.25%	27.12%	33.68%	39.97%	44.27%	48.16%	51.32%	56.43%	59.16%	63.43%
37	18.57%	27.50%	34.04%	40.84%	45.04%	49.24%	51.42%	57.03%	60.49%	63.43%
38	18.87%	27.92%	34.59%	41.47%	45.70%	50.25%	52.54%	58.25%	61.59%	64.08%
39	19.17%	28.28%	35.36%	42.23%	46.12%	51.08%	53.65%	58.40%	62.03%	64.40%
40	19.51%	28.72%	35.83%	42.76%	46.70%	51.77%	54.36%	59.61%	62.91%	65.37%
41	19.79%	29.17%	36.40%	43.28%	47.43%	52.59%	55.38%	59.91%	63.13%	66.02%
42	20.09%	29.62%	36.95%	43.70%	47.94%	53.10%	55.78%	60.97%	64.02%	66.67%
43	20.46%	30.15%	37.59%	44.33%	48.44%	53.86%	56.69%	61.12%	64.46%	67.31%
44	20.72%	30.63%	38.19%	44.87%	48.94%	54.56%	57.10%	61.57%	65.34%	67.64%
45	21.05%	31.03%	38.70%	45.43%	49.63%	55.38%	57.91%	62.18%	66.00%	67.96%
46	21.37%	31.52%	39.17%	45.74%	50.33%	56.01%	58.92%	62.48%	67.33%	68.61%
47	21.68%	31.88%	39.61%	46.16%	51.14%	56.33%	59.84%	63.84%	67.55%	68.93%
48	21.94%	32.30%	40.00%	46.75%	51.56%	57.03%	60.55%	64.15%	67.99%	69.26%
49	22.25%	32.71%	40.50%	47.10%	52.30%	57.85%	61.46%	64.60%	68.21%	69.58%
50	22.56%	33.09%	40.85%	47.60%	52.91%	58.16%	62.27%	64.75%	68.43%	69.58%
51	22.83%	33.44%	41.19%	48.13%	53.45%	58.73%	62.78%	65.05%	68.87%	70.23%
52	23.09%	33.88%	41.68%	48.69%	53.96%	59.11%	63.18%	65.51%	69.54%	70.87%
53	23.38%	34.28%	42.30%	49.05%	54.73%	59.62%	63.79%	66.26%	69.76%	72.17%
54	23.69%	34.66%	42.96%	49.52%	55.38%	59.87%	64.30%	66.72%	69.76%	72.82%
55	23.99%	34.99%	43.34%	50.08%	55.81%	60.32%	64.40%	67.02%	71.08%	73.14%
56	24.28%	35.41%	43.90%	50.68%	56.27%	60.70%	64.81%	67.32%	71.30%	74.11%
57	24.55%	35.91%	44.33%	51.17%	56.54%	61.20%	65.72%	67.32%	71.30%	74.11%
58	24.81%	36.29%	44.75%	51.69%	57.04%	61.96%	66.23%	68.08%	72.19%	75.08%
59	25.08%	36.66%	45.13%	52.14%	57.43%	62.28%	66.63%	68.53%	72.63%	75.08%
60	25.36%	37.05%	45.49%	52.65%	57.97%	62.91%	67.14%	68.68%	73.07%	75.40%
61	25.66%	37.38%	45.93%	52.94%	58.28%	63.29%	67.75%	69.14%	73.07%	75.73%
62	25.90%	37.71%	46.43%	53.72%	58.90%	63.92%	68.36%	69.74%	73.29%	76.05%
63	26.16%	38.06%	46.96%	54.26%	59.36%	64.05%	68.66%	70.35%	73.51%	76.38%
64	26.41%	38.42%	47.47%	54.62%	59.78%	64.56%	68.97%	71.10%	74.17%	77.35%
65	26.65%	38.80%	47.87%	55.00%	60.25%	65.00%	69.27%	71.71%	75.06%	77.67%
66	26.91%	39.08%	48.29%	55.38%	60.63%	65.25%	69.57%	71.86%	75.50%	77.99%
67	27.17%	39.40%	48.78%	55.92%	60.94%	66.01%	69.78%	72.77%	75.94%	77.99%
68	27.44%	39.71%	49.16%	56.25%	61.33%	66.58%	70.18%	73.37%	76.16%	78.64%
69	27.71%	40.04%	49.62%	56.56%	61.75%	67.09%	70.49%	73.83%	76.16%	79.94%
70	27.99%	40.40%	50.10%	56.92%	62.25%	67.72%	70.89%	74.28%	76.60%	80.58%
71	28.25%	40.66%	50.42%	57.39%	62.76%	68.16%	71.40%	74.58%	77.26%	80.58%
72	28.46%	40.99%	50.85%	57.86%	62.91%	68.42%	71.81%	75.04%	77.48%	80.91%
73	28.71%	41.30%	51.17%	58.33%	63.45%	68.61%	72.01%	75.04%	77.92%	80.91%
74	28.91%	41.58%	51.50%	58.64%	63.64%	68.67%	72.41%	75.04%	78.37%	81.23%
75	29.15%	41.90%	51.88%	59.02%	63.95%	68.86%	72.72%	75.79%	78.59%	81.88%
76	29.42%	42.22%	52.37%	59.36%	64.30%	69.18%	73.02%	76.55%	79.03%	81.88%
77	29.70%	42.58%	52.72%	59.85%	64.53%	69.49%	73.53%	77.46%	79.69%	82.52%
78	29.93%	42.96%	53.04%	60.17%	64.88%	70.13%	74.04%	77.61%	80.13%	82.52%
79	30.15%	43.27%	53.40%	60.43%	65.19%	70.38%	74.24%	78.06%	80.35%	83.17%
80	30.38%	43.55%	53.69%	60.81%	65.38%	70.82%	74.54%	78.67%	81.24%	83.50%
81	30.63%	43.85%	54.00%	61.28%	65.69%	71.08%	74.65%	79.12%	81.46%	83.82%
82	30.86%	44.09%	54.44%	61.66%	66.04%	71.33%	74.95%	79.43%	81.68%	83.82%
83	31.10%	44.44%	54.80%	61.95%	66.31%	71.52%	75.25%	79.58%	82.12%	84.14%
84	31.35%	44.73%	55.08%	62.27%	66.69%	71.90%	75.46%	80.03%	82.12%	84.79%
85	31.58%	45.05%	55.36%	62.74%	66.89%	72.09%	76.06%	80.48%	82.12%	85.11%
86	31.84%	45.31%	55.72%	63.07%	67.23%	72.15%	76.27%	80.64%	82.12%	85.11%
87	32.10%	45.64%	56.08%	63.25%	67.58%	72.59%	76.67%	81.24%	83.00%	85.44%
88	32.34%	45.92%	56.37%	63.63%	67.77%	72.91%	76.77%	81.39%	83.22%	85.76%
89	32.56%	46.20%	56.62%	63.83%	67.97%	73.42%	76.77%	81.69%	83.22%	86.08%
90	32.79%	46.51%	56.91%	64.30%	68.31%	73.86%	77.28%	81.85%	83.22%	86.41%

Appendix K: Power Few Cohorts by Age: Cumulative Sum of Harm/Count and Mean Harm/Count per Victim

Harm:

		% of Cohort		Cumulative Sum of Harm		Mean Harm per Victim	
	Age	PF (10%)	NPF (10%)	PF (10%)	NPF (10%)	PF (10%)	NPF (10%)
Harm (10%)	0-9	3.26%	2.71%	45164.5	393909	5018.28	154.29
	10-19	28.62%	13.07%	478253	2566724.25	6053.84	208.27
	20-29	26.09%	20.55%	387195.5	3191616.5	5377.72	164.75
	30-39	18.48%	20.37%	294402	2520974.75	5772.59	131.30
	40-49	13.77%	16.73%	198306.5	1912633.5	5218.59	121.25
	50-59	7.25%	13.60%	92279	1309778	4613.95	102.19
	60-69	1.81%	6.87%	27791	585516.5	5558.20	90.44
	70-79	0.00%	4.03%	0	369138.5	0.00	97.22
	80-89	0.72%	1.70%	13505	192425.25	6752.50	119.74
	90-99	0.00%	0.37%	0	51664.5	0.00	146.77
	100+	0.00%	0.01%	0	188.5	0.00	37.70

		% of Cohort		Cumulative Sum of Harm		Mean Harm per Victim	
	Age	PF (80%)	NPF (80%)	PF (80%)	NPF (80%)	PF (80%)	NPF (80%)
Harm (80%)	0-9	1.67%	2.87%	301730	2351	1430.00	1.00
	10-19	16.30%	12.63%	2520055.5	524921.75	1224.52	50.74
	20-29	20.03%	20.65%	2894437	684375	1144.05	40.46
	30-39	18.46%	20.65%	2226117.5	589259.25	955.01	34.83
	40-49	15.62%	16.89%	1687100	423840	855.09	30.63
	50-59	13.03%	13.66%	1096353	305704	666.07	27.32
	60-69	6.92%	6.84%	481168	132139.5	550.54	23.58
	70-79	4.75%	3.90%	277564	91574.5	462.61	28.64
	80-89	2.57%	1.57%	156760	49170.25	482.34	38.29
	90-99	0.63%	0.33%	37257	14407.5	465.71	52.97
	100+	0.00%	0.01%	0	188.5	0.00	37.70

Count:

	Age	% of Cohort PF (10%)	% of Cohort NPF (10%)	Cumulative Sum of Count PF (10%)	Cumulative Sum of Count NPF (10%)	Mean Count per Victim PF (10%)	Mean Count per Victim NPF (10%)
Count (10%)	0-9	0.06%	2.82%	10	3085	10	1.15
	10-19	14.02%	13.20%	1831	16735	7.86	1.33
	20-29	26.05%	20.47%	3504	26908	8.09	1.38
	30-39	25.45%	20.22%	3485	26104	8.24	1.36
	40-49	17.93%	16.66%	2830	20709	9.5	1.31
	50-59	9.81%	13.61%	1442	16338	8.85	1.26
	60-69	4.39%	6.86%	611	7850	8.37	1.20
	70-79	1.68%	4.04%	274	4512	9.79	1.18
	80-89	0.60%	1.72%	81	1897	8.1	1.16
	90-99	0.00%	0.38%	0	398	0	1.11
	100+	0.00%	0.01%	0	7	0	1.40

	Age	% of Cohort PF (Repeat Victims)	% of Cohort NPF (Repeat Victims)	Cumulative Sum of Count PF (Repeat Victims)	Cumulative Sum of Count NPF (Repeat Victims)	Mean Count per Victim PF (Repeat Victims)	Mean Count per Victim NPF (Repeat Victims)
Count (Repeat Victims)	0-9	1.47%	3.14%	717	2378	2.34	1
	10-19	14.37%	12.90%	8790	9776	2.92	1
	20-29	24.41%	19.51%	15623	14789	3.06	1
	30-39	22.92%	19.59%	14739	14850	3.07	1
	40-49	16.75%	16.67%	10904	12635	3.11	1
	50-59	11.65%	14.07%	7116	10664	2.92	1
	60-69	4.81%	7.37%	2872	5589	2.85	1
	70-79	2.46%	4.42%	1433	3353	2.79	1
	80-89	0.98%	1.90%	536	1442	2.60	1
	90-99	0.17%	0.43%	74	324	2.06	1
	100+	0.01%	0.00%	4	3	2	1