Using the Offenders Index to investigate patterns of offending

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Abstract

The Offenders Index is a rich data source which consists of criminal conviction information collected from the courts. While it has been used to identify, for example, the proportions of particular birth years which have had a criminal conviction, there has been little interest in how the types of offences which offenders are convicted change over time.

In this talk, we describe the problem of identifying patterns of offending behaviour, with the aim of identifying criminal lifestyles and how these might change over time. A latent class approach provides the methodological basis, and allows us to identify group profiles and the likely number of groups. While many offending patterns appear to be single offence, other offenders are involved in a mix of activity, some involving violence and others not. We observe strong changes over time and across birth cohorts, with the proportion of female offenders brought before the courts rising dramatically for some latent classes in later cohorts. While procedural changes offer some explanation of these results, social change will also play a part.
Introduction

The aim of this paper is to provide a general overview of an ongoing research programme on criminal careers which seeks to use the Offenders Index to explore a variety of issues related to changing patterns over time. In our work there are both substantive issues - which involve investigating changes in the patterns of criminal careers over the life course and specifically focusing on the nature of offending - and methodological issues – which involve developing new methods for assessing changes in the nature of offending over time and to take advantage of modern administrative datasets such as the Offenders Index. After a brief summary of some of our work to date, this paper provides some initial thoughts and preliminary findings on disentangling age, period (or year) and cohort (or generational) effects when considering changes over time.

Focusing on age, period and cohort effects highlights our attempt to work on important substantive, methodological and statistical matters relating to criminal careers. The study of criminal careers is a burgeoning research area but understanding age, period and cohort effects is a comparatively neglected area. There are at least three reasons. Firstly, criminologists have not fully grasped the importance of the topic. Secondly, there are methodological issues to confront as datasets are difficult to obtain which can be used to probe the topic. Finally, there are some crucial statistical issues which also need to be addressed. As stated, we present some initial thoughts and preliminary findings. But, first, some of our work so far in the area of criminal careers.

Research to date

Our team has been operative for over fifteen years embracing topics in both crime and health. However, our focus more specifically on criminal careers began with an analysis of a long-term follow-up of white-collar offenders (Soothill et al., 1997; Soothill et al., 1999a) and a similar long-term follow-up of sex offenders (Soothill and Francis, 1997; Ackerley et al., 1998; Soothill et al., 1998; Soothill and Francis, 1999; Soothill et al., 2000; Escarela et al., 2000; Soothill et al., 2002d; Soothill et al., 2005a, b). Our interest then embraced homicide (Soothill et al., 1999b; Francis and Soothill, 2000; Soothill et al., 2002b, 2002d; Francis et al. 2004) together with a specific focus on the media coverage of homicide (Soothill et al., 2002c; Peelo et al., 2004). Methodological issues came to the fore in grappling with the concept of crime seriousness (Francis et al., 2001). In parallel, an interest developed on some specific serious offences (e.g. incest (Soothill and Francis, 2002); arson (Soothill et al., 2004b), perjury (Soothill et al., 2004c); kidnapping (Soothill et al., 2007; Liu et al., 2008)) and more recently on the inter-relationships and sequencing of selected serious offences (e.g. Soothill et al., 2008).

However, throughout the last five years a more general focus on patterns of offending has also emerged (Soothill et al., 2002a; Francis et al., 2004a). Increasingly, we have become interested in the issues of changes over time (e.g. Soothill et al., 2003, 2004a; Francis et al., 2004b; Francis and Soothill, 2005; Francis et al., 2007; Soothill et al., 2008; Soothill et al., in press). It is this latter interest which underpins the substantive and methodological issues raised in this paper. Meanwhile, we were also recognising the importance of comparative work, using other datasets, and linking with other investigators (e.g. Christofferson et al., 2003, 2005, 2007, 2008).
Importance of age, period and cohort models

It is important to clarify why we are interested in trying to separate out the effects of age, period and cohort effects for, as already mentioned, it has not been an issue – with some notable exceptions – that has engaged criminologists. There are probably at least two reasons for this. Mainly it is because, as we shall argue later, criminological explanations have tended – both traditionally and in contemporary times – to be somewhat static. In short, they have tended not to consider or to embrace change. In fact, this has become more of a problem in the last decade or so as criminological discourse, certainly in policy terms, has been increasingly dominated by a psychological framework. With the focus on the individual, societal change has tended to be disregarded. In contrast, sociologists who, for around a quarter of a century from the mid-1960s, provided the dominant discourse in criminology recognised the importance, both potential and actual, of changes within and between societies but rather lacked the wherewithal and the tools to analyse change. The wherewithal consisted of appropriate datasets to attempt to measure change while the tools included the appropriate statistical techniques which needed to be sharpened for the task.

Within this ocean of neglect, one of the important exceptions in focusing upon change was the work of the illustrious, but sadly late, criminologist, Leslie Wilkins who started his career as an engineer, eventually becoming Deputy Director of the Home Office and then subsequently emerging as a famous professor of criminology at the Universities of California and then New York in the United States. Wilkins had the fairly unusual attributes of being a criminologist – his book, Social Deviance: Social Policy, Action and Research, should be regarded as a minor classic – and a statistician. Wilkins’s work on considering so-called ‘delinquent generations’ involved the development of an ingenious dataset and the use of statistical techniques which are both enterprising and challengeable. Certainly his work produced a minor flurry of debate on the methodological foundation of his work which both supported (e.g. Pullum, 1977) and challenged his thesis (e.g. Rose, 1968). In a thoughtful contribution, Farrington brought the debate to a rather premature conclusion by suggesting that Wilkins was proved to be wrong. However, the story is certainly not complete in terms of understanding age, period and cohort effects. Probably most criminologists are perhaps relieved that the matter is not currently a flavour of the month, for the technical issues to confront are undoubtedly daunting. Nevertheless, one should not underestimate its importance criminologically.

In brief, the question is whether changing patterns of crime are due to:

i. **Age effects** The relationship of age to crime is well known. Age effects are often thought of as biological or psychological processes affecting the teenage years, or decreasing parental controls in that period (Farrington, 1986).

ii. **Period or year effects** which affect all ages equally. These could be economic changes, government policy changes, global and national events

III. **Cohort or generational effects** where each generation thinks anew about criminal activity based on unique experiences in childhood. Some researchers have related the birth cohort size to changing criminal activity (see e.g. Maxim (1985), so that increasing crime is associated with larger cohorts and greater competition for jobs.
There may also be age interactions with year if, for example, the government targets certain age groups with policy initiatives.

**Changing patterns of crime**

The phrase, ‘changing patterns of crime’, makes an important assumption, that is, patterns of crime are, indeed, changing. Certainly it seems uncontroversial that over time crime does change. Motoring offences dominate the criminal statistics but, obviously, before the arrival of the internal combustion engine, traffic offences were of a different order. Whether the arrival of the internet actually changes the nature of crime – in other words, new crimes actually emerge – or simply the internet enables old crimes to emerge in a different form (for example, new kinds of deception) is arguable. Nevertheless, there seems little doubt that crime – both quantity and quality – does change over time. Our focus, however, is more specific. We are interested in whether ‘patterns of offending’ change over time. So, for example, is violence increasing while property offences are decreasing? Are violent offenders specialists or are they involved in other activity?

In order to measure changes in patterning, one needs to confront the long-standing problem in criminology, namely, that of classifying criminal behaviour. This is not the place to review this early work but we will simply point to an important distinction. Early work in criminology, say in the 1970s, attempted to *classify a criminal* – thus, an offender might be judged as a robber, a trickster and so on. Don Gibbons (1962) was probably the prime exponent of this approach. The outcome envisaged was that an offender then has that label throughout his or her career and so having all the problems that the label provokes in terms of the difficulty of finding jobs etc. – Lemert (1967) characterises these effects as ‘secondary deviance’. In fact, identifying *criminal* typologies raises many concerns. Certainly very little of this work was based on real life data so the subtle nuances of criminal careers are missed and there were significant issues in deciding how to allocate offenders to a class. In fact, Gibbons himself seemed to present an obituary to this approach in his articles in the *British Journal of Criminology* (1975) and *Criminal Justice and Behaviour* (1988). In short, criminal typologies, becoming close to criminal stereotypes, still may have a resonance in fictional representations, but their use in criminology has been downplayed in recent years.

In contrast, our own work has begun to focus on the classification of *crime*, not the criminal. We are not alone in focusing on this approach, for it underpins routine activity theory (Cornish and Clarke, 1986). However, we are trying to identify *types of criminal activity* in distinct age groups and, hence, this can be seen as embracing a developmental approach. In brief, it allows the development of an offender moving from one crime type to another. So, if one is looking for a criminological pedigree, it essentially follows the approach of Sampson and Laub (1993) in probing pathways through crime.

There is another distinction that is important, namely, whether one analyses patterns and pathways in terms of the *amount* of offending over time or the *type* of offending over time. Most work, particularly in the United States, has focused on the former, namely, the *amount* of offending over time (e.g. Nagin and Land, 1993; D’Unger et al., 1998), while our work on the *type* of offending has been an attempt to provide some sort of counter-balance to this over-riding trend. Of course, in the
longer term, one would like to be able to model both quantity and quality of offending over time, but perhaps it is useful to distinguish these terms analytically at this stage.

Figure 1 (taken from D'Unger et al, 1998) shows a typical outcome of the approach considering the quantity of offending over time using data from Farrington’s study. What it essentially shows is that three offending groups and one non-offending group can be identified. The three offending groups can be identified as an adolescent-limited group, who have highest frequency at age 16, and then decline and stop in their early 20s, and two chronic offending groups – a low chronic and a high frequency chronic group. This typology echoes the theoretical work of Moffitt (1993), who hypothesised such groups.

**Figure 1. Latent classes for the frequency of offending. Source D’Unger et al (1998)**

![Graph showing latent classes for the frequency of offending.](image)

**Typologies of crime**

A rather different approach is to consider the quality or nature of offending over time. Figure 2 shows a simplified invented criminal history of a typical male offender between the ages of 14 and 22 years.

**Figure 2 A simplified criminal conviction history for one offender**

<table>
<thead>
<tr>
<th>age</th>
<th>14</th>
<th>17</th>
<th>20</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offences</td>
<td>Bicycle stealing</td>
<td>Shoplifting; Carrying offensive weapon</td>
<td>Fraud; Petty theft</td>
<td>Fraud; Petty theft; Receiving stolen property</td>
</tr>
</tbody>
</table>

Typologies of crime

A rather different approach is to consider the quality or nature of offending over time. Figure 2 shows a simplified invented criminal history of a typical male offender between the ages of 14 and 22 years.
We would like, for example, to determine whether bicycle stealing and shoplifting tend to co-occur in the cohort of which this offender is a part; similarly, whether fraud and receiving stolen property co-occur, and at what ages these offences are most prevalent. When one is faced with a whole range of criminal histories of this kind, the task is the difficult one of description.

**The Offenders Index data set**

For this study, we use the England and Wales Offenders Index – a Home Office research data set, which is a court based record of the criminal conviction histories of all offenders in England and Wales from 1963 to the current day.

The complete data set is rarely analysed. We analyse data from the Offenders Index Cohort study (Prime et al 1999), taking six birth cohorts born in 1953, 1958, 1963, 1968, 1973, 1978 and followed through to 1999. This birth cohort is an approximate 1 in 13 sample of all offenders born in the sampled years, and samples all offenders born in four selected weeks. The convictions stored are standard list offences – which consists of all indictable convictions and some more serious summary convictions. The index stores dates of conviction, the offence code of the conviction (very detailed) and the disposal or sentence.

The dataset has numerous advantages for examining patterns over time. First, there is a high degree of consistency over time. The definition of standard list offences has not changed dramatically over the 36 years of the study, coupled with this is the length of the database – with over 36 years of data. However, there are disadvantages. First it does not contain information on death, or immigration, or emigration. An individual might have left the country (perhaps to Scotland), but this would be viewed as a period of not offending in the dataset. Secondly, there is the method on which the dataset is formed. The dataset is formed by record matching, taking court records and matching them on name and data of birth to form criminal histories. Although this procedure compares well with police records (Francis and Crosland, 2002; Home Office) it can introduce inaccuracies. Finally there is a problem with all long-term longitudinal datasets – new offences are passed into law, or some offences become viewed as more or less serious and therefore definition of standard list offences change over time We deal with this by removing all offences which become standard list or stop being standard list over the 36 year period.

To carry out our study, we need to simplify the data, reducing the more than 2000 offence codes to 38 major offences, after combining categories. The philosophy we take to do this is to combine offences which are of the same nature but differ only in severity. Thus common assault is combined with other non-lethal violence categories to form a category of assault. Table 1 below contains the 38 offence groups used in the study.
Table 1. The 38 broad offence codes used in the study.

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Lethal violence (including attempts)</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>Violence</td>
<td>21</td>
</tr>
<tr>
<td>3</td>
<td>Firearms/dangerous weapon (possession etc)</td>
<td>22</td>
</tr>
<tr>
<td>4</td>
<td>Resisting arrest etc</td>
<td>23</td>
</tr>
<tr>
<td>5</td>
<td>Kidnapping/false imprisonment</td>
<td>24</td>
</tr>
<tr>
<td>6</td>
<td>Sexual 16+</td>
<td>25</td>
</tr>
<tr>
<td>7</td>
<td>Sexual under 16</td>
<td>26</td>
</tr>
<tr>
<td>8</td>
<td>Sexual consensual</td>
<td>27</td>
</tr>
<tr>
<td>9</td>
<td>Prostitution</td>
<td>28</td>
</tr>
<tr>
<td>10</td>
<td>Burglary (dwelling)</td>
<td>29</td>
</tr>
<tr>
<td>11</td>
<td>Aggravated burglary (dwelling, other)</td>
<td>30</td>
</tr>
<tr>
<td>12</td>
<td>Burglary (other)</td>
<td>31</td>
</tr>
<tr>
<td>13</td>
<td>Going equipped</td>
<td>32</td>
</tr>
<tr>
<td>14</td>
<td>Robbery</td>
<td>33</td>
</tr>
<tr>
<td>15</td>
<td>Blackmail</td>
<td>34</td>
</tr>
<tr>
<td>16</td>
<td>Vehicle taking (aggravated etc)</td>
<td>35</td>
</tr>
<tr>
<td>17</td>
<td>Theft</td>
<td>36</td>
</tr>
<tr>
<td>18</td>
<td>Theft from person</td>
<td>37</td>
</tr>
<tr>
<td>19</td>
<td>Theft by employee</td>
<td>38</td>
</tr>
</tbody>
</table>

**Methodology**

We adopt a latent class approach to the problem of finding patterns in conviction histories. We follow a similar approach to that of Francis et al (2004) who, using 75 summary offence groups rather than 38, examined the 1953 Offenders Index cohort separately for males and females, and found ten distinct patterns of male offending and three classes for females. More recently, (Soothill et al, 2008) we considered conviction patterns in 16-20 year olds over all six cohorts, and found a greater variety of offending types, with 15 classes for males and five for females. This paper will examine all six cohorts over all time periods and thus will use the complete Offenders index cohort data from 1963 to 1999. Figure 3 contains a schematic representation of the dataset analysed, with the yellow shaded cells indicating where data is present.

The latent class methodology conceptually finds hidden classes in offending patterns. We search for classes across all age groups and cohorts, but expect that membership probabilities of any class to change over cohort and age.

Formally within an age group we define a set of indicator variables $O_{ija}$ as follows:
\( O_{ija} = 1 \) if offender \( i \) is convicted for offence \( j \) \
\( O_{ija} = 0 \) otherwise.

We define \( O_{ia} \) to be the prevalence vector for offender \( j \) and age group \( a \) over the 38 broad offence groups.

\[ O_{ia} = (O_{1ja}, O_{2ia}, \ldots O_{ija}, \ldots O_{38ia}) \]

Figure 3. Schematic representation of the Offenders Index birth cohort data.

<table>
<thead>
<tr>
<th>Birth Cohort</th>
<th>Age groups</th>
<th>No. of offenders in cohort</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10-15</td>
<td></td>
</tr>
<tr>
<td>1953</td>
<td></td>
<td>8851 - 2217</td>
</tr>
<tr>
<td>1958</td>
<td></td>
<td>9233 – 2348</td>
</tr>
<tr>
<td>1963</td>
<td></td>
<td>10686 – 2569</td>
</tr>
<tr>
<td>1968</td>
<td></td>
<td>9126 – 1797</td>
</tr>
<tr>
<td>1973</td>
<td></td>
<td>6118 - 1071</td>
</tr>
<tr>
<td>1978</td>
<td></td>
<td>3726 – 665</td>
</tr>
<tr>
<td>No. of offenders in age group</td>
<td>26797 - 4659</td>
<td>47440 - 10667</td>
</tr>
<tr>
<td>Male - female</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Assume there are \( K \) classes, with \( k=1 \ldots K \).

Let \( \pi(k) \) be the probability of membership of class \( k \), and \( p_{jk} \) the probability that there is at least one offence of type \( j \) given that the offender belongs to class \( k \).

Then the likelihood is

\[ L = f(O) = \prod_{i,a} \sum_{k} \pi(k)p(O_{ij}|k) \]

where
\[ p(O_j|k) = \prod_j p_{jk}^{O_{ij}} (1 - p_{jk})^{1 - O_{ij}} \]

Thus, \( \pi(k) \) gives the size of cluster \( k \), and \( p_{jk} \) the definition of class \( k \). We omit age groups from the analysis where there is no offending - where the prevalence vector is all zeros. Such a group would simply be detected as an additional non-offending group and would add additional complexity to the analysis.

We can extend this model to allow for differing probabilities of membership. We replace \( \pi(k) \) by \( \pi(k|a,p,c) \) allowing these probabilities to depend on age \( a \), period \( p \) and cohort \( c \). We use a multinomial model to estimate parameters for each latent class.

\[
\pi(k|a,p,c) = \frac{\exp\{\eta(k|a,p,c)\}}{\sum_k \exp\{\eta(k|a,p,c)\}}, \text{ where } \\
\eta(k|a,p,c) = \text{linear model involving age, period and cohort effects} \\
= \alpha_k + \beta_{ka} + \beta_{kp} + \beta_{kc} (\text{main effects - one possible model})
\]

Within each latent class, there is the well-known problem of parameter identification, as there is a linear indeterminacy between the beta parameters if a full main effects model with age, period and cohort terms is fitted (see e.g. Robertson and Boyle, 1992). However, in this analysis we are not interested in the estimates of the beta parameters, but more in examining model fit to see whether age, period or cohort explains the most variation. To do this, the Bayesian Information Criterion (BIC) is used to determine the best model. BIC is best thought of as a penalised likelihood and is defined by

\[
BIC = -2 \log L + p \log(n)
\]

where \( p \) is the number of parameters in the model and \( n \) the number of observations. As the number of parameters and the complexity of the model increases, the -2 log L term becomes smaller as the fit improves; this complexity is penalised by the addition of \( p \log(n) \) term, which becomes larger as \( p \) increases. The best model is found by taking the model with the minimum value of BIC.

A final consideration is to bear in mind that maximisation of the likelihood is often a difficult problem. We deal with this by taking 300 different starting value sets for each model and choosing the best fitting model from these results.

**Results**

We analyse the full data on female convictions across the six cohorts. We adopt a strategy as follows:

a) fit a model with no covariates first of all, and determine the number of classes by choosing the model with the lowest BIC. This gives a minimum BIC value at 11 classes.
b) fit covariate latent class models to models around the 11 class solution. We fitted a variety of models to the 11 class and 12 class solutions. The models included

i) full interaction models fitting a parameter for each age-period-cohort combination

ii) main effect age+period+cohort factor models

iii) two factor models such as age+period

iv) one factor models

Table 2 shows the BIC values for a variety of models. This strategy found that the 12 class solution with age and cohort effects but not year effects gave the best fit with the lowest BIC value.

<table>
<thead>
<tr>
<th>Covariate model</th>
<th>BIC 11 classes</th>
<th>Number of parameters</th>
<th>BIC 12 classes</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>all interactions model</td>
<td>110533.51</td>
<td>738</td>
<td>110553.86</td>
<td>808</td>
</tr>
<tr>
<td>age and cohort</td>
<td>109501.20</td>
<td>608</td>
<td>109412.63</td>
<td>665</td>
</tr>
<tr>
<td>age and year</td>
<td>109071.50</td>
<td>558</td>
<td>109124.18</td>
<td>610</td>
</tr>
<tr>
<td>age and cohort</td>
<td>109063.47</td>
<td>538</td>
<td><strong>108932.36</strong></td>
<td>558</td>
</tr>
<tr>
<td>cohort and year</td>
<td>109301.99</td>
<td>548</td>
<td>109320.05</td>
<td>599</td>
</tr>
<tr>
<td>Age</td>
<td>109618.70</td>
<td>488</td>
<td>109675.27</td>
<td>533</td>
</tr>
<tr>
<td>Year</td>
<td>109506.85</td>
<td>498</td>
<td>109477.04</td>
<td>544</td>
</tr>
<tr>
<td>Cohort</td>
<td>110210.38</td>
<td>478</td>
<td>110156.74</td>
<td>522</td>
</tr>
<tr>
<td>None</td>
<td>110594.98</td>
<td>428</td>
<td>110717.40</td>
<td>467</td>
</tr>
</tbody>
</table>

Based on these results, we choose the 12 class solution for female offending with the probabilities of group membership varying by age and cohort. It is important to point out that the number of groups for female offending patterns is substantially larger than the five groups found in our study of the 16-20 year olds. On closer examination, this appears to be reasonable. Firstly, we are analysing substantially more offenders - 10667 females rather than the 4659 females used in Soothill et al (2008b). Secondly, we expect new classes of offending to appear to represent patterns which appear in later life but which are uncommon in 16-20 year olds.

We first examine what these typologies are by looking at the class profiles $\rho_{jk}$, and then examine the changing proportions of specific typologies and how they change over age and time.
The 12 classes can be divided into three groups - single offence classes, paired offence classes and versatile classes.
There are six specialist offence classes.

- Shoplifting (29% of offender-age groups)
- Theft (9.7%)
- Violence (7.7%)
- Criminal damage (5.4%)
- Theft from meters (1.7%)
- Drugs possession (3.9%)

The specialist offence classes are characterised by having a high $p_{jk}$ for a single offence and a low $p_{jk}$ for all other offences. Thus the shoplifting cluster has a high probability of shoplifting and low probabilities for all other offences in that particular cluster.

Three paired offence groups:

- Resisting arrest and absconding/bail offences (7.1%)
- Receiving and handling with some shoplifting (4.4%)
- Theft by employee with some fraud (2.8%)

The paired offence classes are characterised by having a high $p_{jk}$ for a two offences and a low $p_{jk}$ for all other offences. Thus the receiving and handling cluster has a high probability of receiving, a probability of shoplifting of around 0.4, and low probabilities for all other offences.

Three versatile groups

- Fraud with theft and receiving (12.7%)
- Theft with burglary and shoplifting (acquisitive non-violent - 9.0%)
- Violent acquisitive (shoplifting, theft with some violence – 6.6%)

The versatile offence classes are characterised by having a high $p_{jk}$ for more than two offences and a low $p_{jk}$ for all other offences. Thus the violent acquisitive cluster has high probabilities of shoplifting and also of theft, with a probability of violence of around 0.4, and low probabilities for all other offences.

We can see that the shoplifting class is the most prevalent ($\pi(k)=0.290$), followed by the versatile offence class of “Fraud with theft and receiving” ($\pi(k)=0.127$) and the specialist offence class of theft ($\pi(k)=0.097$). However, these are overall figures taking the prevalence rate over the entire sample; and we know from the statistical model for $\pi(k)$ that the prevalence varies by age and cohort.

To illustrate this, we examine the prevalence rate of the specialist violence class, which has an overall prevalence of $\pi(k)=0.077$ across all cohorts and age groups. Table 3 shows the estimated prevalence rates across age and cohort.
Table 3. Changing proportions of the violence only female offending group.

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Age 11-15</th>
<th>16-20</th>
<th>21-25</th>
<th>26-30</th>
<th>31-35</th>
<th>36-40</th>
<th>41-45</th>
</tr>
</thead>
<tbody>
<tr>
<td>1978</td>
<td>0.29</td>
<td>0.18</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973</td>
<td>0.18</td>
<td>0.13</td>
<td>0.09</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1968</td>
<td>0.15</td>
<td>0.07</td>
<td>0.09</td>
<td>0.11</td>
<td>0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1963</td>
<td>0.07</td>
<td>0.05</td>
<td>0.05</td>
<td>0.07</td>
<td>0.14</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>1958</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.13</td>
<td>0.09</td>
</tr>
<tr>
<td>1953</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
<td>0.03</td>
<td>0.05</td>
<td>0.0</td>
<td>0.15</td>
</tr>
</tbody>
</table>

In this table, the cohort effects are rows, the age effects are columns and the year effects are top-left to bottom-right diagonals. We can see that the highest proportion is observed in the 1978 birth cohort for those aged 11-15. 29% of those convicted in that age group and cohort are estimated to be violence specialists. In contrast, we see that the 1953 cohort is in general not involved in violence, with the exception of the oldest age group. The large proportion in this group is because of the relative paucity of convictions for this combination of age group and birth cohort. In general, we see an increasing propensity for membership of this class over the cohorts but also some evidence of a year effect.

Figure 4 shows the same information in the form of a contour plot.

Figure 4 Contour plot for the female probability of membership of the class “Violence”
We can look at two more of the classes. Figure 5 contains the contour plot for the versatile group of Fraud, theft and receiving, and Figure 6 contains the contour plot for criminal damage.

**Figure 5 Contour plot for the probability of female membership of the class “Fraud with theft and receiving “**

In Figure 5, we can see a strong age effect for the versatile fraud/theft group peaking in 26-30 age group, and also some evidence of a cohort effect. In Figure 6, in contrast, we see a strong year effect with increasing probability of belonging to this group up to the early 1990s, and some tentative evidence of a decline in the late 1990s.

**Discussion and Conclusions**

David Smith is a criminologist who appreciates the issues raised in this paper. He reminds that “just describing the relationship between age and crime is more difficult than might at first appear because differences between age groups reflect both developmental change and shifts between historical epochs” (Smith, 2002). He goes on to define age, period and cohort effects, while also reminding that “there are substantial conceptual, and hence, mathematical, difficulties in trying to disentangle these three effects”. He provides some examples of the potential problems by
pointing out that “even if one variable (age or period) is held constant, the resulting trends confound two of the effects”. In particular, he reminds of the difficulties in using cross-sectional data which holds the period constant and where the confounding involves ageing and cohort effects. In contrast, the usual type of longitudinal data which involves comparing rates of offending at different stages of the life cycle for the same cohort of individuals born in a given year has the possible confounding of ageing and period effects. So how does our approach of using multi-cohorts over a long time-span measure up in responding to the implicit challenge set up by Smith. In brief, to what extent have we managed to disentangle age, period and cohort effects and what are the substantive results?

Latent class analysis has enabled us to determine 12 distinct classes of offending for female offending. The covariate analysis has identified that the major changes over time on female offending are age and cohort effects, with little evidence of a year by year effect. However, there are exceptions. Some offending classes, notably criminal damage, seem to show a strong year effect. This suggests that the analysis needs to be improved and more sophisticated models developed, with interactions of class with age, period and cohort needed. In general, however, our
methodology can give real insight into changes in the proportion of convictions across different typologies of crime.

Finally, some caveats. It is important to remember two things. Firstly, the proportions of offenders are not numbers of offenders and do not necessarily represent increasing violent crime – the number of females convicted of a crime are declining in the most recent cohorts in our study.

Secondly, the figures represent system changes as well as social change. Thus for minor offences, young people are diverted away from the court system into cautioning for later cohorts. This will lead, for example in the more recent years of a lower proportion of 10-15 year olds being convicted of shoplifting and a higher proportion being convicted of more serious offences.

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