Changing crime-mix patterns of offending over the life course: A comparative study in England & Wales and the Netherlands.

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Abstract

This chapter presents a comparative analysis of England and Wales and the Netherlands through examining criminal lifestyles through conviction data and how they change with age. The analysis has used latent Markov modelling to jointly estimate the crime mix patterns (different offenders have different selections of offences) and the transition probabilities (offenders move from one pattern to another or desist as they age). We discuss issues relating to comparing the two datasets, including definitions of offences in the two jurisdictions and the year of birth distribution of the two samples. We investigate whether some crime mix patterns are more specialized than others in terms of their long term patterns, and whether offenders belonging to some crime patterns are likely to desist earlier than others.

Introduction

Criminal career research has focused upon describing and explaining offending over the life course. This research has created valuable information to help with our understanding of criminal offending. However, the majority of knowledge accumulated about criminal careers has been gathered from a small number of studies which have some serious limitations (Piquero, Hawkins, & Kazemian, 2012). Furthermore, the studies in this area have been heavily dominated by US researchers, yet there are a number of European countries that have excellent data resources for studying criminal careers. Hence, there is scope for addressing some of the current limitations of criminal career research with evidence from outside of the United States. Using official conviction data from England & Wales and the Netherlands, this study will illustrate the value of cross-national comparisons in providing new insights into some familiar problems in criminal career research.

Criminologists have certainly explored criminal trajectories or pathways showing the long term patterns of criminal activity over time. The majority of this research has focused on looking at the *frequency* of offending and how these frequency trajectories change with age, but have tended to ignore any changes in the *patterns* and *types* of offences being committed. However, studying patterns of offending behaviour in detail is important for several reasons. For example, it allows us to identify which offence typologies appear to be precursors for other types of offences (Francis, Soothill, & Fligelstone, 2004). Such information has both practical and theoretical implications. Knowing what types of offences criminals may commit prior to being involved in serious crime like murder, for example, can be of great importance to law enforcement agencies and policy makers as there may be scope for targeting such offenders before they move on to the more worrying pathways of criminal activity. Further, understanding possible links between various types of crime also has a theoretical force, which may enable us to distinguish between different types of offenders. In short, gaining detailed knowledge of crime mix patterns – which is the main focus of this chapter - may well help with our understanding of offending behaviour and the causes behind it.

Crime mix (the variety of different offences committed over the period of time), is a criminal career dimension that has been explored by other researchers, (Block, Blokland, van der Werff, van Os, & Nieuwbeerta, 2010; Piquero, Farrington, & Blumstein, 2003; Piquero, Farrington, & Blumstein, 2007). Crime mix patterns refer to the different types of offences committed by an individual within an age period and the particular offending characteristics or styles these individuals hold. The crime mix patterns can be thought of as different groups or classes of offending, where the individuals belonging to that group all share similar patterns of offending styles.

In this chapter we aim to build upon the latent transition analysis methodology used by Bartolucci et al. (2007) and Francis et al., (2010) to identify the crime mix patterns and to see how offenders transition between such groups as they age in both England and Wales and the Netherlands. Unlike

Francis et al. (2010), we will also be focusing on both male and female offenders. Our aim is therefore to try and identify if there are any common patterns of offending behaviour in the two countries.

Prior Research

Previous criminal careers research has explored a wide range of topics relating to patterns of criminal activity over the life course, (Barnett, Blumstein, Cohen, & Farrington, 1992; Blumstein, Cohen, & Farrington, 1988a; Farrington, 1986; Gottfredson & Hirschi, 1988; Moffitt, 1993; Nagin, Farrington, & Moffitt, 1995; Sampson & Laub, 2003). Within the paradigm of criminal careers there are many parameters to consider, however for the purposes of this chapter we are choosing to focus only on three, which are relevant for the study of crime mix patterns;

1. Criminal typologies – the classification of offenders into different groups based on the type of activity they are involved in.
2. Onset age – the age when these offenders engage in criminal activity, and which has been identified as playing a significant part in their subsequent criminal career.
3. Specialisation versus versatility – whether offenders focus on certain types of crime or commit a variety of different crime types.

Criminal Typologies

The criminal career paradigm has led to a number of typological theories for explaining the different patterns of offending. For many years, researchers have tried to distinguish offenders from non-offenders by classifying offenders into criminal typologies (Gibbons, 1975; Moffitt, 1993). This was in an attempt to try and understand the causes of crime and criminal behaviour by defining offenders based upon their offending patterns (Vaughn, DeLisi, Beaver, & Howard, 2008). More recently, offenders are now usually defined by a number of characteristics such as the length of their criminal career, the type and seriousness of their offences and the mix of crime types they engage in (Sullivan, McGloin, Ray, & Caudy, 2009).[1]

One popular typological theory was proposed by Moffitt (1993). This theory of dual taxonomy states that varying patterns of offending, based upon offences committed, can be used to define specific groups of offenders. Moffitt suggested there are two types of offenders with distinct criminal pathways. The smaller group was referred to as the 'Life Course Persisters' (LCP) who engage in offending at an early age and continue to offend at a steady rate forming a rather flat trajectory path over the life course. According to Moffitt, the LCP group are more likely to be versatile in their

[1] Sexual offending is rather different, with some researchers proposing an ad hoc division into rapists and child molesters (e.g. Prentky et al.,1997; Hanson, 2002) based on the index offence in the sample. This approach ignores that many offenders commit both crimes, and also a wide range of non-sexual offences.

offending and commit more serious offences. The second group are the 'Adolescent Limited' (AL) offenders consisting of a larger number of offenders who commit their first offence in their teenage years but peak in early adulthood and begin to decrease their offending and desist. This group are involved in less serious offences such as vandalism and public order offences (Moffitt 1993:695). Moffitt's original theory unfortunately does not consider many quantitative properties about either of the two groups of offenders. For example, it is unknown what percentage of offenders will be either 'life course persistent' or 'adolescent limited', the frequency of offending for each group at different ages or the length of the criminal careers (MacLeod, Grove, & Farrington, 2012) although the proportions in each group has been assessed by group based trajectory modelling on offending data (See e.g. D'Unger, Land, McCall, & Nagin, 1998).

Taking into account the typologies based on frequency of offending is important, but it is also useful to examine the typologies of offence mixes which give more detailed information of the vast amount of offending behaviour, (Soothill, Francis, Ackerley, & Humphreys, 2008). Classifying *offenders* into categories such as a 'burglar' however, gives them a label and therefore does not allow for changes over time. We consider the most appropriate way forward is to use an approach that embraces dynamic changes; classifying offending patterns within a specific time window is beneficial as it allows for changing crime mix patterns.

Onset age

An important factor when examining the longitudinal patterns of offending, is the relationship between age and crime (Bartusch, Lynam, Moffitt, & Silva, 1997; Brame & Piquero, 2003; Farrington, 1986; Piquero, Paternoster, Mazerolle, Brame, & Dean, 1999a). In particular, the age at which an individual begins offending has received considerable attention in the study of criminal careers (Farrington et al., 1990; Farrington, Snyder, & Finnegan, 1988; Loeber & Leblanc, 1990; Moffitt, 1993; Piquero & Chung, 2001). This is often referred to as onset, representing the beginning of a criminal career. Many studies have shown offenders that have an early onset age tend to have a lengthy criminal career (Blumstein, Cohen, Roth, & Visher, 1986; Farrington et al., 1990; Piquero, Brame, & Lynam, 2004). Other findings have shown that those with an early onset age are also more likely to be chronic offenders, engage in more serious crimes and be more versatile in their offending (DeLisi, 2001; Mazerolle, Brame, Paternoster, Piquero, & Dean, 2000; Piquero et al., 1999a). This early onset offender group resonates with Moffitt's 'Life Course Persisters'. Knowing the age at which an offender starts to commit crimes is therefore a key part in the prediction of an individual's crime mix pattern. It is also important to policy decision makers because they want to target those individuals who are most likely to be serious offenders.

The majority of the research on offending and criminal careers has been concentrated on adolescents and younger offenders (Piquero et al., 2007). This ignores any offending patterns that occur in adult and older offenders. Delisi and Piquero (2011) point out that some studies have produced evidence that chronic offenders do not necessarily have an early onset age. They claim that groups of chronic adult offenders exist, who did not start their criminal careers until they were adults and also can engage in serious crimes. These offenders with a late onset age are often referred to as 'late bloomers' (Thornberry, 2005). Delisi (2006) also found that in a sample of adult offenders, a large portion were not first arrested till they reached adulthood[2]. McGloin et al., (2009) produced a study that looked at identifying changes in offending over time, and showed the importance of examining patterns of offending over a wider range of ages. They suggested that some offenders may prefer particular offence types over a shorter period of time, but eventually due to a number of changing factors, they become more versatile over the entire course of their criminal careers.

Specialisation and versatility

Investigating different crime mix patterns for evidence of specialisation or versatility is important for understanding the processes that cause criminal activity over the life span. It is also of interest to policy makers, as knowing the extent to which offending patterns are specialised can help with tackling a certain type of crime by focussing on a particular type of offender (Nieuwbeerta, Blokland, Piquero, & Sweeten, 2011). Also as Farrington et al., (1988) stated, it is important to understand specialisation, as being able to recognise early offence types in an individual's criminal career would assist in predicting future offences. However, past research has showed that studies tended to discover extensive evidence of versatility in offending patterns (Blumstein, Cohen, & Farrington, 1988b; Britt, 1996; DeLisi, 2005; Farrington et al., 1988; Loeber & Leblanc, 1990; Piquero et al., 2003; Wolfgang et al., 1972). Despite that evidence of specialisation in offending was very limited, the research of specialisation continued due to its importance in policy decisions (Sullivan et al., 2009). Due to the way past studies considered specialisation, versatility in offending became the dominant view. However, Sullivan et al,(2009) pointed out that defining the term specialisation is important because it influences how it is measured and this in turn has consequential effects on study's findings. For example, specialisation can be defined by measuring the amount that an offender keeps committing the same type of offence in a direct successive order (Kempf, 1987). However, some researchers believe this definition is too restrictive, referring to specialisation as "stability in offending types" (Francis et al., 2004). Therefore an offender is considered a specialist if they display concentration on particular types of offences, which is observed over a specific period of time. More recently, evidence of specialisation has been discovered for some offenders (Francis et al., 2010; Francis et al., 2004; Lussier, LeBlanc, & Proulx, 2005; McGloin et al., 2009; Osgood &

[2] Despite these findings on adult onset offending, McGee and Farrington (2010) found that even though some offenders appeared to have an older onset age for offending, it did not necessarily mean that they were adult onset offenders. It is possible that these offenders had been involved in criminal activity as adolescents or even earlier but this had either gone undetected or did not warrant involvement by law enforcement agencies.

Schreck, 2007; Sullivan, McGloin, Pratt, & Piquero, 2006). Piquero et al. (2003) reviewed some studies that found evidence of specialisation when the categories of offending were split into violent and non-violent categories. Unfortunately, this methodology ignores any variability that may occur within the violent or non-violent categories: in effect, the categories are too broad and will miss more nuanced forms of versatility. This means that many offenders who do change the type of offence they commit within these broad categories would be mistaken as repeating the same offence and considered a specialist offender. Deciding upon an appropriate number and relevant offence categories is of great importance as it significantly affects the conclusions reached.

Extant methods for assessing specialisation are varied - Sullivan et al (2009) provides a review -, but dominant methods include the Forward Specialisation Coefficient (Farrington, 1988) and the diversity index (Piquero et al, 1999). An alternative approach to specialisation is through the concept of criminal lifestyles (Francis et al, 2010). Extending the methodology used previously to identify offence clusters in the Francis et al (2004) paper, this study proposed the use of latent transition analysis (a form of latent Markov modelling to examine the transition of female offenders switching offence clusters over time. Offenders can then be seen as specialised if they remain in the same offending cluster from one period of time to another or versatile if they switch clusters. The results showed that some female offenders do switch offending clusters and become more versatile as they age. This study also showed that using latent class analysis and latent transition analysis to examine offending behaviour is worthwhile in gaining insights about the patterns of criminal activity over time.

Socio-demographic and criminal justice issues in England & Wales and the Netherlands

There are both similarities and differences in the social and demographic structure of the two countries under study[3]. The population of England and Wales, at an estimated 56.6 million in 2012, is considerably larger than the Netherlands with an estimated population of 16.8 million in 2013. Both countries have similar life expectancy from birth, with males expecting to live till 79 and females till 82 (England and Wales 2010-2012, Netherlands 2007-2010).

There are important differences in the criminal justice systems of the two countries. In terms of court procedure, an adversarial system is used in England and Wales, whereas an inquisitorial system is used in the Netherlands. For the period under study both have police forces with a regional command structure (43 in England & Wales and 25 in the Netherlands – as of January 2013 the Netherlands has one National Police), who are responsible for recording crimes that are reported to them. In

[3] Unless otherwise indicated, statistical data used in this section were obtained from the Office for National Statistics (http://www.statistics.gov.uk) for England and Wales, and the Netherlands' Central Bureau of Statistics (http://www.cbs.nl) for the Netherlands.

comparison to other European countries, the Netherlands criminal justice system has often been viewed as rather mild and tolerant, especially in regard to its criminal policies concerning drugs (Tak, 2008). However during the 1970s, 1980s and 1990s, police recorded crimes have increased rather substantially, having nearly quadrupled from 1970 to 2005 (Tonry & Bijleveld, 2007). England and Wales drugs policy prior to the 1960's followed the 'British system" which was an arrangement whereby drugs were available to addicts prescribed by Doctors, who regulated the distribution of illicit drugs of the Dangerous Drugs Acts 1920 and 1923. However, from 1960 there was an increase in the prevalence of drug users and new illegal substances became available in the UK. This led to several new pieces of legislations being passed that increased the control over illicit drugs. By 1971 the Misuse of Drugs Act (MDA) was passed which categorised drugs into classes based on their levels of harm. It also made it an offence for intent to supply and stricter penalties were imposed for trafficking and supply.

Drug policy in the Netherlands, in contrast, is rather unique in Western counties, with the main focus on preventing the use of 'hard' drugs, reducing harm and limiting the risks to users (Tak, 2008), rather than prosecuting and criminalising drug use. Drug use is treated more as a public health issue, rather than a criminal problem (Farrell, 1998). The main law for drugs is the Opium Act (amended 1976) which distinguishes between drugs with unacceptable risks (hard drugs) such as cocaine opiates and amphetamines, and those with acceptable risks (soft drugs) such as cannabis. Although the use and possession of 'soft' drugs is a misdemeanour offence, the Netherlands have a tolerance policy where possession of small quantities of cannabis for personal use is not prosecuted (Leuw, 1991) . The priorities for law enforcement resources are normally concentrated on investigating and prosecuting the production and trafficking of drugs (Tak, 2008).

Gun ownership may also be an important background variable to certain types of crime. Figures from the Swiss-based Small Arms Survey Survey (2007) suggest that there are between 470,000 legal and illegal firearms in the Netherlands and between 2,000,000 and 4,700,000 firearms in England and Wales. This gives average firearms rates of 3.9 guns per 100 people in the Netherlands and 6.2 guns per 100 people in England and Wales. While both rates are low compared to the USA rate of 88.8 guns per 100 people, the England and Wales rate is around 50% higher than the Netherlands rate.

Crime statistics as recorded by the police have been compared across Europe (Aebi et al., 2010) and show that both countries are seeing a steady decline in crime rates (from 2003 to 2007). England and Wales have a slighter higher crime rate with 9,156 total offences per 100,000 population (2007), compared to the Netherlands figure of 8439 total offences per 100,000. However, when examining offences separately, there are bigger variations between the two countries. For drug offences, The Netherlands only have 94 offences per 100,000 persons compared to the England Wales rate of 423 per 100,000.

For most of the 20th Century, welfarism typified the youth justice system in England & Wales. This meant the needs of the offending child were the main priority rather than punishment. However, by the 1970s the welfarism approach came under heavy criticism, claiming that it placed strong limitations on individual rights as well as being regarded as lenient and unsuccessful (Muncie and Goldson, 2006). There was a call for more justice based models to be implemented based on the principles of a ‘just deserts’ approach which was focused on punishing the offence rather than the person.

During the 1960s, the Netherlands also implemented a ‘welfare system’ into the juvenile justice system. This meant many juvenile offences tended to be dealt with away from court and the police usually opted for diversionary measures when dealing with young offenders, leading to big reductions in number of court orders placing juveniles in institutions (Junger-Tas & Block, 1988). As in England and Wales however, from the 1980s to the 1990s, this juvenile criminal law system started to be heavily criticised and was considered outdated and too overprotective (Tak, 2008). This led to a number of changes to juvenile criminal law in 1995 with more emphasis on punishment.

Aim of the Chapter and Research Questions

Our goal is primarily focused upon finding crime mix patterns and how they develop over the life course, within two longitudinal datasets of criminal conviction histories from England & Wales and The Netherlands. Using a latent Markov modelling approach, we can examine the criminal careers of offenders in more depth by exploring both the crime mix patterns of offenders and how these develop and change over time.

By developing the methodology used in Francis et al (2010), where the idea of lifestyle specialisation and short-term crime typologies (crime mixes) over five-year age-periods was introduced, we can apply a latent Markov model to identify different crime mix patterns and also estimate the transition probabilities in the datasets. Latent transition analysis has become more popular in the analysis of criminal career data as it shows the different phases of criminal careers and the transition between each phase, (Massoglia, 2006; McGloin et al., 2009). The methodologies of latent transition analysis and latent Markov modelling are identical, and we use the second term in this paper except when referring to previous work.

Our central research questions are as follows:

- What similarities and differences can be identified between England and Wales and the Netherlands? In terms of the criminal offending of young people?
- What common patterns of offending behaviour can be identified in England and Wales and the Netherlands?
- Do the probabilities of transition vary across countries?

Method

Data Sources

Two longitudinal datasets of conviction histories have been used in this study. The first dataset is the Offenders Index (OI) database for England and Wales. The full Offenders Index contains the court convictions of all offenders from 1963 to the end of 2008. A subset of the Offenders Index consisting of the criminal histories of offenders eight birth cohorts (1953, 1958, 1963, 1968, 1973, 1978, 1983 and 1988), each representing a four week sample (around a one in thirteen sample) of all offenders born in a specific year. The data is collected from age 10 with histories followed up till 2008. Not all offences form part of the OI- with only offences that are considered 'standard list' offences are included. 'Standard list' offences are those which are considered indictable (crown court offences) or triable either way (either in the magistrates court or the Crown court and the more serious summary (magistrates court) offences. Therefore many minor offences, such as numerous motoring offences, are excluded. The OI dataset contains a limited amount of information on each individual. This includes the date of birth, age at conviction, gender, offence code, dates of court appearances, the number of convictions at each appearance and the disposal outcome.

The second dataset is from the Netherlands, and consists of conviction data from the Criminal Careers and Life-Course Study (CCLS), which is an extensive study carried out by the Netherlands Institute for the Study of Crime and Law Enforcement (Blokland, Nagin, & Nieuwbeerta, 2005). The dataset contains criminal career information of a 4% random sample of all criminal cases adjudicated by a judge or public prosecutor in 1977 in the Netherlands. Given their high prevalence, DUI-cases were undersampled (2%), whereas more serious offenses, like drug, violent and sexual offenses were oversampled (25%-100%). It follows individuals from age 12 right through till 2002. This means that many offenders were above the age of 50 at the end of the follow up. Unlike the England and Wales dataset, this dataset contains a wider range of offences and includes more minor offences.

Challenges in cross national comparisons

As we are trying to identify features of similarity or differences in criminal career patterns across two different datasets we need to control both for known criminal justice system differences and for sample differences. We first consider the criminal justice system differences. England and Wales use the adversarial system and the Netherlands use the inquisitorial system. Additionally, during the 1960s, the Netherlands tended to predominantly use diversionary methods away from court for juveniles when compared to England and Wales. Prison sentences are also usually much shorter in the Netherlands and custodial sentences are less likely than in England and Wales. The age of criminal responsibility is also different, being age 12 in the Netherlands and age 10 in England and Wales.

Turning now to sample differences, we note that the different sampling methodologies mean that the year of birth distribution varies greatly between the two datasets. The Netherlands dataset has a wider range- from 1912 to 1965 – and with all offenders having a conviction in 1977- whereas the England and Wales dataset has one of 8 pre-specified years of birth, with convictions in any year from age10 up to 2008. To reduce any generational differences we have taken offender samples only from the 1953, 1958 and 1963 cohorts as they include offenders who can have a conviction in 1977.

There are also differences in offence categories. Thus, the England and Wales dataset uses a complex coding system with over 500 offence codes offence codes and documented in the Home Office Offenders Index codebook (Home Office, 1998) The Dutch dataset bases its offence classification on the Dutch legal code and the offence types are registered by the Dutch Ministry of Justice – 28 categories are used.

Alignment of the two datasets

The previous section highlighted the problems in ensuring that the two samples are as identical as possible before analysis. To align the datasets, we adopted the following strategy.

a) Common start age of offending
   For the England and Wales sample, all offences prior to age 12 (the age of criminal responsibility in the Netherlands) were excluded.
b) Similar years of birth of the two samples
   We restricted the Dutch data to those with years of birth within two years or less of the three birth cohort years used in the England and Wales data. The Netherlands data was therefore restricted to include only those with a year of birth between 1951 and 1965 making them aged 12-26 in 1977 and also with at least one valid conviction in the 11 offence categories between ages 12-26. This condition will minimise any generational or year of birth differences in the two samples.
c) A conviction in 1977
   As the Netherlands sample all had at least one conviction in 1977, cases in the England and Wales sample without a conviction in 1977 were excluded.
d) Alignment of offence categories.
   The alignment of offence categories was challenging. Coding manuals were examined to determine which offences in the England and Wales dataset best aligned with those in the Netherlands dataset. In addition, the categories for both the Netherlands and the England and Wales datasets were collapsed Furthermore, some of the more minor offence categories in

the Dutch dataset which did not exist in the England and Wales data were omitted. This led to 11 common offence categories across the two jurisdictions which were similar in nature.

The Netherlands data contained 2222 offenders once the above restrictions had been imposed and this was significantly less than the sample for England and Wales cohorts even after the restrictions had been imposed. Latent class analysis and latent Markov modelling tend to detect more groups if the sample size is larger, and so a final alignment condition was to make the sample sizes equal in the two datasets. A random sample of 2222 offenders across the three cohorts was therefore taken from the England and Wales dataset.

Data preparation

We adopted a similar approach to the Francis et al (2010) study, dividing the conviction histories into 3 five-year age groups (12-16, 17-21 and 22-26), but analysing males and females together. We focused on this age range for two reasons. Firstly, we believed from earlier work (Francis et al 2010) that there would be a large amount of transiting between various crime mix groups in this age range. Secondly, we wanted to reduce computational complexity by examining only three age groups. In total, the individuals in both dataset samples accumulated 13162 convictions over the 15 year period. Recalling that each offender has a conviction in at least one of the age groups, Tables 1 and 2 shows the number of offenders for each of the 11 offence categories across the three different age periods. There are slightly more male offenders in the Netherlands data sample[4], which may explain why the total number of convictions is higher, as past research shows that males commit more crimes than females (Blumstein et al., 1986; Piquero et al., 2003). Overall, the majority of offenders offended in the 17-21 year age group; however this is not the case for all offence categories. For example, drug offenders are more prevalent in the 22-26 age period. This would agree with the findings from Massoglia (2006) who also discovered that drug offences increased after the transition into adulthood. There are a number of other differences between the two datasets that can be noticed. The Netherlands has a higher proportion of offenders offending in each age group, and has a substantially higher number of offenders for sexual offences, blackmail, robbery, drugs and public order offences. The England and Wales dataset has lower proportions of offenders in each age group and therefore is lower than the Netherlands for most of the offence categories except for fraud and forgery. Burglary

[4] The Netherlands data sample contained 95% male offenders and 5% female offenders; The England and Wales data sample contained 81.5% male offenders and 18.5% female offenders.

and theft was the most common category in both datasets. The drugs category was the 5th most common and blackmail the lowest category for both datasets.

To obtain more information on the offenders' crime mix patterns we must both identify which offence categories are likely to co-occur and also to identify the membership of individuals to crime mix patterns over the 15-year period. To be able to do this we must use a latent class approach.

<TABLE 1 HERE>
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Statistical Analysis

As already discussed, we first divided the criminal careers of each offender into 5 year time periods. We started at age 12, which is the age of criminal responsibility in the Netherlands (age 10 in England and Wales). Five-year time periods allow a reasonable amount of time for an offender to accumulate offences so that an understanding can be gained of the varied nature of their offending, while still allowing for the offender to switch behaviour. Thus, any changes in criminal activity and pathways can be assessed as offenders get older, making it possible to check for periods of specialization, versatility or non-offending.

To be able to identify crime mix patterns in the data, latent Marvov modelling is used. We first describe the latent class analysis model, and then extend the model to allow transitions to be included.

The Latent Class Model

A set of binary indicator variables were constructed to indicate whether there was a conviction for each of the 11 offence categories in each specific time period for each offender. The binary indicator had the value of 1 if a conviction for that offence category occurred and 0 if not. Within each age period, we look at which of the J=11 offence types have had convictions to get a response pattern. The end data file produces a prevalence matrix of offence categories by person-time period strips.

Let O_{ijt}be the observed binary response for offender *i* and offence category *j* in time period *t*, with $O_{ijt} = 1$ if offender *i* has at least one conviction for offence category *j* within time period *t*, and 0 if not. We define $\boldsymbol{O_{it}} = (O_{i1t}, O_{i2t}, \dots, O_{iJt})$ to be the vector of responses for each time period for each offender we assume there are K clusters or classes within the dataset.

Let class *k (k = 1 …K)* have probability *π(k)*, and $p(\mathbf{O}_{it}|k)$ is the probability of observing the indicator vector O_{it} given member ship of class k.

The likelihood is then

$$L = f(\mathbf{O}) = \prod_{it} \sum_{k} \pi(k) p(\mathbf{O}_{it}|k)$$

And, under the assumption of conditional independence, we can assume that

$$p(\mathbf{O}_{it}|k) = \prod_{j} p_{jk}^{\boldsymbol{O}_{ijt}} (1 - p_{jk})^{1-\boldsymbol{O}_{ijt}}$$

Is a product of Bernoullis, where $p_{jk}$is the probability that there is at least one conviction for offence category *j* in any time period, given that the offender belongs to class *k*.

The unknown parameters – the p_{jk} and the– $\pi(k)$ – which are obtained by finding the true maximum of the likelihood. As there are many unknown parameters to estimate, finding the true maximum of the likelihood becomes complex. We ensure as far as possible that the global maximum of the likelihood is reached by using 100 different start sets and taking the best solution.

To be able to determine the optimal number of latent classes K, we have used the Bayesian Information Criterion (BIC) statistic. The BIC is based upon the likelihood and addresses the problem of over fitting by the addition of a penalty term based on both the number of parameters and the sample size.

We chose the value of K that minimises the BIC, which is defined to be:

$$BIC = -2\log L + v\log(n),$$

Here *v* is the number of parameters and *n* is the number of offenders. After reaching model convergence, it becomes possible to obtain the posterior probabilities that an offender *i* belongs to one of the latent classes *k* in a specific time period *t*. This can be given by q_{ikt} where

$$q_{ikt} = \frac{\pi(k)\prod_j (p_{jk})^{O_{ijt}}(1-p_{jk})^{1-O_{ijt}}}{\sum_{k=1}^{K}\pi(k)\prod_j (p_{jk})^{O_{ijt}}(1-p_{jk})^{1-O_{ijt}}}$$

q_{ikt} provides different estimated probabilities for each offender for each time period.

Latent Markov modelling

As described above, Latent Class Analysis makes the assumption that the time periods within an individual's criminal history are independent, and this is an unrealistic assumption – there is likely to b dependence between an offenders criminal patterning at adjacent time points.
We therefore extend the Latent Class model to a Latent Markov model (LMM), of which Latent transition analysis is a special case (Bartolucci, 2013). Latent Markov modelling (LMM) incorporates an extra set of unknown transition matrices, each of which gives the probability of membership of a latent class membership at one time point t given latent class membership at the previous time point *t-1*, (*t*=2,…*T*) which are estimated along with the other parameters. . LMM is based on Markov chain models (Kaplan, 2008; Langeheine & Van de Pol, 2002) and captures the discrete stages of individuals' movement of latent states through time. A consequence of that is that membership of a latent class at time *t* depends only on the observed data and membership at time *t-1*, and not at any earlier time points.

Unlike the above LCA models, classes in Latent Markov models are usually known as latent *states.* In these Latent Markov models the transition probability parameters show how switching between the different latent states occurs from time *t-1* to time *t*.

As before, we let O_{ijt} represents the observation of the ***j***th indicator variable of interest at time point *t* for an individual *i*. We now set $\boldsymbol{O_i} = (\boldsymbol{O_{i1}}, \boldsymbol{O_{i2}}, \dots, \boldsymbol{O_{it}})$ to be the complete set of indicator responses over the *T* time periods.

Let s_t denote a state of the latent variable at time point *t*, where $1 \leq s_t \leq K$. Let $T(s_0)$ be the initial state probabilities, and let $T(s_t|s_{t-1})$ represent the latent transition probabilitie from time (t-1) to time t. and $p(\boldsymbol{O_{it}}|s_t)$ is the probability of observing the indicator vector O_{it} at time t given member ship of state s_t The LMM model is therefore;

$$P(\boldsymbol{O}_i) = \sum_{s_1=1}^{K}\sum_{s_2=1}^{K} \dots \sum_{s_T=1}^{K} T(s_0)\prod_{t=2}^{T} T(s_t|s_{t-1})\prod_{t=1}^{T} p(\boldsymbol{O}_{it}|s_t).$$

with the likelihood equal to

$$L = \prod_{i=}^{n} P(O_i)$$

We again assume conditional independence, and, as before set

$$p(\boldsymbol{O_{it}}|s_t) = \prod_{j} p_{js}^{\boldsymbol{O}_{ijt}}(1-p_{js})^{1-\boldsymbol{O}_{ijt}}$$

where $p_{js}$is the probability that there is at least one conviction for offence category *j* in any time period, given that the offender belongs to state s. Note that the p_{js} do not vary over time – the latent states remain static and do not change definition – it is the offender who is able to switch between these static latent states.

The latent Markov model, therefore, needs to estimate three sets of probabilities; the initial state probabilities *T(s₀)*, the transition probabilities and the p_{js}.

Results

We report on the results of fitting a separate latent Markov model to each dataset in turn. We first fitted a sequence of models to determine the optimal number of states for the LMM analysis. Table 3 shows the log-likelihood and associated BIC values for various Latent Markov models for the England and Wales and Netherlands datasets specifying from one state up to seven-states. The lowest BIC value was achieved for the five state model for the England and Wales dataset - however a six state model minimised the BIC for the Dutch dataset. As we wanted to specify the same number of groups for both countries to allow comparability, we chose the more parsimonious 5 state model to investigate further in each dataset.

<INSERT TABLE 3 HERE>

One important issue is whether the two jurisdictions can be fitted with common parameters – in other words whether the same model works for both England & Wales and the Netherlands. The BIC for the combined sample is 66106.36; the sum of the BIC values for separate five-state fits to England and Wales the Netherlands datasets is 66611.41 – a difference of over five hundred. The evidence that separate models are needed for England & Wales and the Netherlands is extremely strong, suggesting that different processes are taking place in the two jurisdictions.

Interpreting the latent states

Table 4 and Table 6 show the profiles of the five latent states for respectively England and Wales and the Netherlands datasets. Formally, the tables contain the probabilities p_{js} of an offender in one of the latent states *s* having one or more convictions for a particular offence category *j*. It is immediately apparent that some latent states have higher probabilities for particular offences than for others.

To understand these probabilities, we take an example. The estimated probability that an England and Wales offender in state 3 having the offence 'burglary and theft' is 0.9992; suggesting that most of the offenders assigned to state 3 will have a conviction in the 'burglary and theft' category. The next highest probability for state 3 was for 'fraud and forgery', with just over 15% chance of offenders having this offence. The rest of the offence categories in state 3 had probabilities of 8% or lower. Therefore state 3 is considered a specialist 'burglary and theft' offending group. Even though there is a number of offenders who have specialised 'burglary and theft' offending, there are still many offenders for whom 'burglary and theft' offences are just one in a wide range of different types of convictions within the five year period.

Thus, using these estimated probabilities, the five latent states were given a label that best summarized the crime mix of offences in each state. These labels should only be used as an indication of the crime mix but we use these as a short-hand indication of the profile of the latent state.

For the England and Wales dataset, only one state can be considered to be specialized (state 3 – burglary and theft) with a very high probability for burglary/theft and low probabilities for all other offences. However, there are two very low offending groups- state 1 with a very low probability for all offence types which we take to be a "no offending" group, and state 4, with low probabilities for nearly all offences but with a slightly higher probability for burglary/theft. It is worth bearing in mind that although we state that the burglary/theft offending group is specialised, this is only suggesting that these offenders may prefer to commit certain crimes over other types of crimes. The Netherlands dataset also has one state that is considered to be specialised (state 3 –burglary and theft), with three being more versatile and the remaining state – state 1- a very low offending group with very low probability of convictions for all offences

<INSERT TABLE 4 HERE>

<INSERT TABLE 5 HERE>

<INSERT TABLE 6 HERE>

<INSERT TABLE 7 HERE>

Transition Probabilities

We would expect to see the majority of offenders to be actively offending during the second age period 17-21 years, as past research has proven this to be the peak age of offending (Farrington, 1986; Hirschi & Gottfredson, 1983; Moffitt, 1993). Therefore we predict most offenders will be at some point in the 'non-offending/low offending group', most likely at age 12-16 years and again at age 22-26 years. However some offenders will start their criminal careers at a much earlier stage and we predict that these offenders will continue offending as they grow older and become involved in more serious and a variety of offences (Mazerolle et al., 2000; Moffitt, 1993; Piquero et al., 2007; Piquero, Paternoster, Mazerolle, Brame, & Dean, 1999b).

Tables 8 and 9 show the estimated transition probabilities for a time heterogeneous Markov model (that is, the transition probabilities vary over time) for England and Wales and the Netherlands. They describe how the offending behaviour changes from age period 12-16 years to 17-21 years, then again from age period 17-21 years to 22-26 years.

Transition probabilities in the England and Wales dataset

The initial state values at age 12-16 years (the first line of Table 8a) give the estimated sizes in terms of probability of the five states in the 12-16 age group. The first state -the 'non offending' group - is the largest group at age 12-16 for England and Wales (Table 8a first row). At the first transition 34% remain in this group and the majority move to the 'burglary/theft specialist' group. For the second transition almost all the offenders in state 1 move into other offending groups. The majority of these late starters move onto the 'burglary/theft specialist' group and 'low offending with some violence, drugs, fraud/forgery, criminal damage' group.

The majority of offenders who start in state 2, the 'low offending with some violence, drugs, fraud/forgery, criminal damage', move into the 'Low rate offending with some burglary or theft' group in the first transition. However only 35% remain in state 2 in the second transition, and the majority move into the 'non offending' group and desist from offending.

Offenders beginning in state 3- the 'burglary/theft specialist' group - tend to move into the 'low rate burglary/theft' group and over 40% move into the 'low offending with some violence, drugs, fraud/forgery, criminal damage' group, with 16% moving into the 'versatile and more serious offending' group. However in the second transition, 87% move into the 'non-offending' group, which is something that we would expect after the peak age of offending.

Most offenders in the England and Wales dataset begin in state 4, the 'low rate burglary/theft' group. In the first transition hardly any remain and over 81% move into the 'versatile and more serious offending' group. In the second transition, 80% then move to the 'non-offending' group showing desistance after adolescence.

State 5, the 'versatile and more serious offending' group, begins as the second smallest group. In the first transition, the majority remain within this group and the more offenders join this group during the 17-21 age period. In the second transition just under half remain in this group, with almost a third moving to the 'low rate with some violence, drugs, fraud/forgery, and criminal damage' group showing de-escalation in severity and frequency rather than desistance.

Transition probabilities in the Netherlands dataset

Like the England and Wales dataset, the first state -the 'non offending' group - is the largest group at age 12-16 for the Netherlands (Table 9a first row). Results show that the majority of offenders (82%) belong to the first state 'non-offending/low offending group'. Examination of Table 9b shows that, as expected, most of these offenders transition into one of the other offending groups for the age period 17-21 years. The majority move into the burglary/theft specialist group (37%), and a smaller number (12%), move into the 'versatile and more serious offending' group. During the second transition into age period 22-26 (Table 9c), those who were still in the 'non-offending/low offending group', have a high probability (67%) of moving into the 'drugs and burglary' group, with a smaller number (17%) moving into the 'versatile and more serious offending' group.

The small number of offenders who start in state 2 'low rate with some violence, sexual offences and criminal damage' tend to stay in this group with nearly 98% remaining for the first transition and 82% in the second transition. Those who do not remain in this group for the second transition, tend to move into the 'non-offending/low offending' group, possibly desisting from crime after peak offending age. In the second and third age periods many other offenders from other groups move into state 2, increasing its size rather significantly to include 35% of all offenders. State 2 is a very stable state with very few offenders actually switching to other states over the three time periods.

For offenders in state 3, the 'burglary and theft specialist' group, the majority move into the 'versatile and serious offending' group, with only 35% remaining in the group and another 17% moving into the ‘low rate offending with some violence, sexual offences and criminal damage’ group. In the second transition even fewer remain in state 3 and the majority now move into the ‘non-offending/low offending’ group.

Only a very small number of offenders begin in state 4, the ‘versatile and more serious offending’ group. At the first transition 39% remain within this group and therefore continue with the serious and versatile offending. However 38% move to the ‘burglary and theft specialist’ group and 23% move to the ‘low rate with some violence, sex offences and criminal damage’ group, therefore continuing offending but less versatile and serious. During the 17-21 age period, offenders from other states move state 4, increasing its size significantly. In the second transition, even more remain in state 4 and 21% move into the ‘drugs and burglary/theft’ group which is a less versatile group but still more diverse than the other groups. Those offenders who do stay in state 4 tend to continue offending.

A small group of offenders begin in state 5, ‘drugs and burglary/theft’ group. It is also one of the most stable states over the three age periods with the majority remaining within this state. For the first transition 93% remain in the second transition 72% remain, with 21% moving into the ‘non-offending/low offending’ group. Most offenders who start or join state 5 appear to stay within this group over the three age periods.

Summary of transition probabilities

A different set of patterns emerge for each of the two jurisdictions. In England and Wales, none of the states show stability over the three time periods. The most stable state is 5. The small number of offenders who begin in this state have a high chance of continuing with their versatile offending particularly during the second age period. The offenders in state 5 have a very low chance of desisting, with hardly any moving into the ‘non-offending/low offending’ group.

Offenders in states 2, 3 and 4 all have high probability of desistance with the majority moving into the ‘non-offending/low offending’ group after the peak age of offending. The offenders in state 1 are likely to move into the ‘burglary/theft specialist’ group and even show evidence of some late starters who do not switch states till the third age period.

Most offending takes place during the second age period and therefore lots of switching to the criminally active states occurs in the first transition. Much more desistance occurs in the third age period showing a significant decrease in offending after the peak age.

The Netherlands have two crime mix groups that show stability and persistence over the three time periods. States 2 and 5 both show that those offenders with an early onset age are likely to continue with offending and stay specialised within their chosen domain of offending.

For the other states we see different transition patterns emerging. For the offenders in state 3 we also see that early onset indicates persistence in offending but these offenders can escalate and progress onto more versatile offending during the peak age of 17-21 years. However they will then have a high probability of desisting once they reach the third age period.

The small group of offenders who are in state 4 also show that early onset is an indicator of persistence in offending. However the persistent offending is not necessarily in the same state or domain of offences. The offenders in state 4 show a lot of switching between states, suggesting very versatile offending behaviour. As state 4 is already a very versatile crime mix group, it is not surprising that these offenders switch states, although this is more likely in the second age period. During the third age period there appears more stability in state 4 with more offenders remaining.
<INSERT TABLE 8 HERE>
<INSERT TABLE 9 HERE>
<INSERT TABLE 10 HERE>

From the latent Markov models we were also able to examine the individual posterior probabilities of state membership to see what offending group each individual offender belonged to for each time period. This allowed us to check which transition patterns (pathways through the offending groups) were the most popular. There were a possible 125 pathways for offenders to take through the five offending groups. There were a possible 125 pathways for offenders to take through the five offending groups. The England and Wales offenders took 41 pathways and the Dutch offenders took 43 of these pathways.

The most common pathway for England and Wales offenders was to start in the ‘low burglary and theft/non-offending’ group and move to the ‘low violence, drugs, fraud/forgery, criminal damage’ group for age 17-21 years and then move into the ‘non-offending/low offending’ group for the last age period. The most common pathway for the Dutch offenders was to start in the ‘non-offending/low offending’ group and to join the ‘low violence, sex offence and criminal damage’ and to continue in this group for the second two age periods. Although these pathways are somewhat similar in that the first transition from an almost non-offending group into a relatively low offending group, the second transition is different. The England and Wales offenders move again to an almost non-offending group, when the Dutch offenders continue in the same group.
The second most common pathway for both countries is again almost identical, and almost the same number of offenders from each dataset took this pathway. These offenders could be considered as following the age- crime curve. They start in the ‘non-offending/low offending’ group and move into the ‘burglary theft specialist’ group for age 17-21 years and then move back to the ‘non-offending/low offending’ group after adolescence. This also agrees with the adolescent limited offender typology suggested by Moffitt (1993) and explains why a large proportion of offenders have taken this pathway.
The third most popular pathways for each country are considerably different. The third England and Wales pathway shows offenders beginning in the first age period ‘burglary and theft specialist’ group and then moving into the ‘low burglary theft/non offending’ group during 17-21 years and then the

‘non offending/ low offending’ group for the last age period. . The third Dutch pathway is almost the opposite and shows late onset offenders with them staying in the ‘non-offending/low offending’ group for the first two age periods and only joining the ‘drugs and burglary/theft’ group in the last age period.

Conclusion and key findings in the chapter

The purpose of this chapter was to provide a comparative analysis of England and Wales and the Netherlands through conviction data, identifying crime mix patterns and how offenders may switch between these with age. We wanted to investigate if there were any common patterns of offending behaviour and if the probabilities of transition vary across the two countries.

By examining the two longitudinal datasets of criminal conviction histories, containing information of the types of offences, we found several distinct crime mix patterns.

Evidence was found of specialized and versatile crime mix patterns over time for both datasets. Some offenders tended to stay in the same crime mix offending group over each 5 year age period; whereas other offenders would switch groups over time. The make-up of the crime mix groups varied for each dataset along with the transition probabilities, showing differences between the two countries.

We found that our results indicate that the models chosen to examine the datasets were suitable for revealing the patterns of offending. Using the BIC we decided that the 5 state model was the best fit for the datasets using our 11 offence categories observed at three 5 year age periods. The 5 latent states were easily interpretable and the sizes were estimated at each age period.

From clustering the 11 offending categories into 5 crime mix offending groups, we found that certain offences clustered together for both datasets e.g. ‘Murder and Violence’ tended to co-occur with ‘Criminal Damage’, and ‘Fraud and Forgery’ co-occurred with ‘Burglary and Theft’. However for England and Wales we discovered that there was a group which consisted of ‘Murder and Violence’, ‘Criminal Damage’, ‘Fraud and Forgery’ and ‘Drugs’. As for the Netherlands, they also have a group consisting of ‘Murder and Violence’, ‘Sexual Offences’ and ‘Criminal Damage’. Both the datasets have different offence compositions of their versatile offending groups. Some of these crime mix groups are common with other latent class results within criminology

Certain crime mix groups can be interpreted as specialized; both datasets have a specialised burglary and theft group with a very high probability (over 0.9) of an offender having committed this offence if they belong to this group. There are also very versatile crime mix groups identified with a number of different offence categories co-occurring.

We estimated two transition matrices for each sample, the first one from ages 12-16 to 17-21 years and a second one from 17-21 to 21-26 years. We have discovered that most offenders tend to begin offending in the 17-21 year age period usually followed by desistance for the next age period. This is typical of the criminological literature on the age-crime curve and the “adolescent limited” typology suggested by Moffitt (1993). One common route or pathway through the crime mix groups for both datasets, tend to see many offenders moving into the burglary and theft specialised group for the first transition and then desisting after the second transition. Although there are 125 possible pathways that offenders can take through the crime mix groups, there are a few that display evidence of specialization by continuing to offend in the same crime mix group for the next age periods. This is true for 5% of the England and Wales sample where the offenders can be considered low rate chronic as they continue to offend in the 'low offending with some violence, drugs, fraud/forgery, criminal damage' group.

Onset age plays an important part in the crime mix pattern of an offender. As mentioned most offenders start their criminal behaviour during late adolescence, however we have discovered evidence for a small group of offenders[5] who have a late onset age and continue offending into adulthood (although we have a cut off at age 26 we cannot say if they desist or continue from this age). There is also evidence to show that early onset can lead to escalation (continuing to offend at a more versatile manner and commit more serious offences as they grow older).

Our results show that specialization can occur over the shorter term but can also be versatile over the longer term by changing crime mix offending groups and agree with the results of Sullivan et al (2006). This indeed is one of the benefits of using 5 year age periods to assess criminal histories rather than summarising full lifetime of convictions. This contradicts life course theory, which tends to assume that offenders become more specialised as they age (Lussier et al, 2016).

There are caveats to this work that need mentioning. As already stated, differences between jurisdictions may be caused by different recording practices and different criminal justice systems in the two countries, or, alternatively, may represent real differences in offending behaviour caused by the distinctive cultures, education and social systems in the two countries. These are difficult to disentangle without different research using different methodology. To take one example, the larger proportions of those convicted for violence and firearms offences in the Netherlands could be caused by real social differences, yet could also be due to their differing diversionary policies (with more non-violent offences in the Netherlands perhaps not being prosecuted but diverted into other disposals). This important question of what drives these differences will for the moment have to remain unanswered.

Finally, we touch briefly on the theoretical implications of our work. We focus on the routes to desistance in the Netherlands and England and Wales. In England and Wales, states 3 (Theft and burglary specialist) and 4 (low-rate offending) have high probabilities of transiting into state 1 (the non-offender group) at the third time period. This is consistent with Moffitt's theory which suggests

[5] Approximately 8% of the Netherlands offenders and 15% of the England and Wales offenders remained in the "non-offending" states for ages 12-16 and 17-21 years, only moving into an active offending state for 22-26 years.

that adolescent –limited offending tends to be more concerned with criminal damage and property offending rather than violent offending. Similar results can be seen for the Netherland, where state 3 has the highest probability of desistance for 17-21 year olds (transiting into state 1). However, the results are not quite so clear –cut as we also observe that state 2 (low offending with some violence and drugs) in England and Wales also has a high probability of desistance at the third time point. It appears that other, low offending groups are also capable of stopping offending once adolescence is complete.

A Postscript

Professor Keith Soothill sadly died during the production and writing of this manuscript. We are all grateful to Keith for the inspiration and insights into criminal careers research and the personal support he gave to each of us.

Short Biographies

Amy Elliott is a PhD student in Applied Social Statistics at Lancaster University. She has a BA (Hons) Criminology and has worked as a communication and crime recording officer for North Yorkshire Police and interned as a research officer in the crime patterns team at the Home Office. Her research interests include evidence based policing, life course criminology and criminal career research. She is currently a research assistant in the criminal justice partnership project at the University of Central Lancashire.

Brian Francis, is a Professor of Social Statistics in the Department of Mathematics and Statistics, Lancaster University and Associate Director of the Violence and Society UNESCO Centre. He has over 30 years of experience of statistical consultancy and applied statistical research with over 200 research papers and seven co-authored books. His statistical interests are in statistical modeling, the analysis of ranked data, data visualization, case-control studies, and statistical computing, with applications in the social sciences, medicine, and local government finance. He has worked extensively in criminology, developing analytic approaches for research problems, particularly in the areas of criminal careers and crime seriousness and escalation.

Keith Soothill , who was Emeritus Professor in the Department of Sociology at Lancaster University, sadly died in February 2014. His research interests were broad including medical sociology, the sociology of sport, but most of all criminology. He was part of the Lancaster Centre for Youth, Crime and Community, and in 1991 became Head of the Department of Applied Social Science. He has published over 300 articles and numerous chapters and books on criminal careers, sexual crimes, serious offenders and homicide.

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Table 1: Number of Netherlands offenders convicted of specific offence categories on each five year period (N=2222)

Offence	12-16 years	17-21 years	22-26 years	Average number of offenders over the three age groups	% of total offenders
Murder/Violence	99	539	510	383	17.2%
Firearms	5	108	161	91	4.1%
Authority	10	145	127	94	4.2%
Sexual Offences	102	191	140	144	6.5%
Blackmail	7	46	33	29	1.3%
Robbery	19	135	115	90	4.0%
Burglary/Theft	705	1260	866	944	42.5%
Fraud/Forgery	82	297	278	219	9.9%
Criminal Damage	87	394	275	252	11.3%
Drugs	5	185	314	168	7.6%
Public Order	43	257	154	151	6.8%
Total	2222	2222	2222	2222	100.00

Note: offenders can contribute to more than one offence category.

Table 2: Number of England and Wales offenders convicted of specific offence categories on each five year period (N=2222)

Offence	12-16 years	17-21 years	22-26 years	Average number of offenders over the three age groups	% of total offenders
Murder/Violence	113	368	261	247	11.1%
Firearms	16	81	44	47	2.1%
Authority	11	83	44	46	2.1%
Sexual Offences	18	48	25	30	1.4%
Blackmail	3	3	1	2	0.1%
Robbery	21	44	20	28	1.3%
Burglary/Theft	673	1017	593	761	34.2%
Fraud/Forgery	136	418	271	275	12.4%
Criminal Damage	197	414	249	287	12.9%
Drugs	5	122	123	83	3.8%
Public Order	0	23	23	15	0.7%
Total	2222	2222	2222	2222	100.00

Note: offenders can contribute to more than one offence category.

Table 3: Likelihood and BIC statistics for various latent Markov models

Latent Markov Models	Log-likelihood	-2 log likelihood	BIC
Netherlands			
1 state	-21053.3	42106.52	42191.29
2 state	-19273.8	38547.67	38755.73
3 state	-18951.5	37902.96	38265.15
4 state	-18691.1	37382.18	37929.32
5 state	-18527.8	37055.54	37818.46
6 state	-18341.3	36682.67	37692.18
7 state	-18237	36473.95	37760.88
England and Wales			
1 state	-15403.5	30806.99	30891.76
2 state	-14562.3	29124.53	29332.6
3 state	-14343.2	28686.44	29048.63
4 state	-14126.1	28252.15	28799.29
5 state	-14014.9	28029.81	28792.72
6 state	-13902.1	27804.15	28813.66
7 state	-13808.5	27616.89	28903.82
Combined Datasets			
5 state	-32637.4	65274.83	66106.36

Figures highlighted in grey show the lowest BIC value for each dataset.

Table 4: Netherlands estimated probabilities p_{js} of an offender in each state having a conviction in the specified offence

Netherlands	State				
	1	2	3	4	5
Murder/Violence	0.0111	0.1713	0.0951	0.9983	0.0352
Firearms	0	0.0279	0.0444	0.1410	0.1162
Authority	0	0.0442	0.0623	0.1402	0.0518
Sexual Offences	0.0295	0.1233	0.0745	0.0924	0.0070
Blackmail	0.0019	0.0022	0.0190	0.0673	0.0088
Robbery	0	0	0	0.3804	0
Burglary/Theft	0.2236	0.0737	0.9054	0.8082	0.6658
Fraud/Forgery	0.0218	0.0332	0.1642	0.2538	0.2529
Criminal Damage	0.0097	0.1169	0.2135	0.329	0.0616
Drugs	0.0001	0.0252	0.0112	0.1601	0.5373
Public Order	0.0031	0.0560	0.1307	0.2318	0.0392

.Figures in lighter shading are greater than or equal to 0.1 but less than 0.5; those in darker shading are greater or equal to 0.5

Table 5: interpretation of the Netherlands five latent states based on the estimated probabilities in Table 4.

Netherlands	LM States
State 1 –	Non-offending/low offending
State 2 –	Low offending with some violence, sexual offences and criminal damage
State 3 –	Burglary and theft offending
State 4 –	Versatile and more serious offending
State 5 –	Drugs and burglary/theft offending

Table 6: England & Wales estimated probabilities p_{js} of an offender in each state having a conviction in the specified offence

England and Wales	State 1	2	3	4	5
Murder/Violence	0.0082	0.2478	0.044	0.0397	0.3664
Firearms	0	0.0395	0.0025	0.0036	0.0998
Authority	0.0025	0.0514	0.006	0.0028	0.082
Sexual Offences	0	0.0354	0.0028	0.0107	0.0351
Blackmail	0	0.0013	0.0007	0.0017	0.0028
Robbery	0	0.0111	0.0047	0.0098	0.0637
Burglary/Theft	0.0019	0.093	0.9992	0.1046	0.9374
Fraud/Forgery	0.0192	0.1494	0.1557	0.0376	0.4243
Criminal Damage	0.0155	0.2459	0.0818	0.071	0.39
Drugs	0.0026	0.1094	0.005	0.0015	0.1164
Public Order	0	0.0255	0	0	0.0162

.Figures in lighter shading are greater than or equal to 0.1 but less than 0.5; those in darker shading are greater or equal to 0.5

Table 7: Interpretation of the England & Wales five latent states based on the estimated probabilities in Table 6.

England &Wales	LM States
State 1	Non offending
State 2	Low offending with some violence, drugs, fraud/forgery, criminal damage
State 3	Burglary and theft specialist offending
State 4	Low rate offending with some burglary or theft
State 5	Versatile and more serious offending

Table 8: Netherlands estimated state membership probabilities, and transition probabilities from one age period to the next

a) Estimated state membership probabilities

	State	1	2	3	4	5
Age period	12-16 years	0.816	0.044	0.123	0.015	0.001
	17-21 years	0.082	0.304	0.351	0.159	0.103
	22-26 years	0.210	0.360	0.110	0.144	0.177

Note: The 12-16 probabilities are estimated directly from the model as $T(s_1)$. The 17-21 and 22-26 age period membership probabilities are calculated from the $T(s_1)$ and the transition probabilities.

b) Transition probabilities from 12- 16 to 17-21 years

		17-21 years				
	State	1	2	3	4	5
12-16 years	1	0.1006	0.2901	0.3694	0.1207	0.1192
	2	0.003	0.9764	0.0044	0.0146	0.0015
	3	0.0002	0.172	0.3541	0.435	0.0387
	4	0.0017	0.2258	0.3826	0.3875	0.0024
	5	0.0141	0.035	0.0127	0.0107	0.9276

c) Transition probabilities from 17-21 to 22-26 years

		22-26 years				
	State	1	2	3	4	5
17-21 years	1	0.0022	0.0105	0.1442	0.1741	0.6691
	2	0.1742	0.8246	0.0002	0.0004	0.0005
	3	0.3826	0.2188	0.1999	0.1608	0.038
	4	0.0006	0.184	0.1785	0.4245	0.2124
	5	0.2143	0.0084	0.0004	0.0574	0.7195

Note: Figures in lighter shading are greater than or equal to 0.1; those in darker shading are greater or equal to 0.5.

Table 9: England and Wales estimated state membership probabilities, and transition probabilities from one age period to the next

d) Estimated state membership probabilities

	State	1	2	3	4	5
Age period	12-16 years	0.337	0.020	0.215	0.379	0.049
	17-21 years	0.127	0.315	0.219	0.130	0.209
	22-26 years	0.474	0.239	0.130	0.040	0.117

Note: The 12-16 probabilities are estimated directly from the model as $T(s_1)$. The 17-21 and 22-26 age period membership probabilities are calculated from the $T(s_1)$ and the transition probabilities.

e) Transition probabilities from 12- 16 to 17-21 years

		17-21 years				
	State	1	2	3	4	5
12-16 years	1	0.3406	0.0024	0.6044	0.0001	0.0526
	2	0.0038	0.0071	0.0017	0.8336	0.1538
	3	0.0006	0.0012	0.0691	0.5246	0.4045
	4	0.0286	0.8112	0.0008	0.0001	0.1594
	5	0.0231	0.1309	0.0004	0.0144	0.8311

f) Transition probabilities from 17-21 to 22-26 years

		22-26 years				
	State	1	2	3	4	5
17-21 years	1	0.0001	0.4746	0.5241	0.0002	0.0011
	2	0.5676	0.3513	0.0104	0.0474	0.0233
	3	0.8703	0.0019	0.0956	0.0066	0.0257
	4	0.7956	0.0121	0.1094	0.0742	0.0086
	5	0.0057	0.3163	0.1207	0.0647	0.4926

Note: Figures in lighter shading are greater than or equal to 0.1; those in darker shading are greater or equal to 0.5.

Table 10: The three most common pathways for the Netherlands and England & Wales datasets

Dataset	Transition Pattern (12-16 → 17-21→ 22-26)	Frequency	%
Netherlands	State 1 → State 2 → State 2	560	25.2
	State 1 → State 3 → State 1	421	18.9
	State 1 → State 1 → State 5	137	6.2
England and Wales	State 4 → State 2 → State 1	454	20.4
	State 1 → State 3 → State 1	445	20
	State 3 → State 4 → State 1	214	9.6