Home Office

The heroin epidemic of the 1980s and 1990s and its effect on crime trends - then and now: Technical Report

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Summary

- A variety of factors have been cited to explain the rise and fall in crime that has occurred in many nations since 1980. But as yet, no definitive explanation has been produced. In the UK context, a rise and fall in illicit drug use has not been especially prominent in this debate, perhaps due to a lack of robust data for the whole period.

- This paper gathers available evidence and conducts new analysis to try and assess the effect that heroin and crack-cocaine[1] use may have had on acquisitive crime (i.e. theft-type offences) in England and Wales since 1980. It also suggests implications for future crime trends.

- Numerous sources of evidence agree that the number of heroin users increased markedly through the 1980s and early 1990s and that many also used crack as their drug-using career developed. This “epidemic” spread from area to area but the national peak probably occurred between 1993 and 2000. Crime peaked between 1993 and 95.

- Current data, particularly from treatment providers, show that heroin/crack use has declined in recent years and that – as with offending – the decline has been most marked amongst younger people. This means those who began using these drugs during the epidemic still dominate the heroin/crack-using population today.

- Studies agree that, in aggregate, heroin/crack users commit a large number of offences; large enough, this paper shows, to be an important driver of overall crime trends.

- Studies disagree about whether it is drug use that *causes* the criminality. This is because a sizable proportion of heroin/crack users do not resort to theft. And many were offending before taking these drugs. However, evidence suggests that, for at least some users, heroin/crack was the catalyst for offending, and for others it probably accelerated and extended their criminal career. Thus aggregate-level change in numbers of heroin/crack users is likely to affect crime trends.

- An examination of the considerable regional and international variation in crime trends, particularly geographical areas where the crime drop wasn’t marked or the peak occurred at a different time, also points to a possible causal relationship, rather than simple correlation.

- Within England and Wales, the starkest example of regional variation was Merseyside, which had a recorded acquisitive crime peak five years before other police force areas. Evidence also suggests

[1] Hereafter we refer to crack-cocaine simply as “crack”.

Merseyside was one of the first areas to be hit by the heroin epidemic and the first to mount a concerted treatment response.

- Acquisitive (and total) recorded crime in Scotland peaked in 1991, which studies suggest is in line with the national peak in heroin/crack use. But in Edinburgh and its surrounding region (Lothian & Borders), recorded acquisitive crime peaked seven years earlier, in 1984. Data show that Lothian and Borders had a severe heroin epidemic at this time, which was not prolonged into the 1990s as in parts of Scotland.

- Like Merseyside and Edinburgh, Ireland suffered a short, sharp heroin epidemic in the early 1980s and crime surged at this time. Northern Ireland did not have a heroin epidemic and its crime trend was much flatter over the period.

- In the US, all types of crime fell from 1991 but the US crime survey shows that property crime peaked over a decade earlier, in line with the US heroin epidemic. Likewise, many east European nations had a heroin epidemic about a decade after those in western Europe. Eastern Europe also had a recorded acquisitive crime peak around a decade after Western Europe.

- Two approaches were used in this paper to estimate the effect of heroin/crack use on crime. Both suggest that the epidemic may have had a significant impact on acquisitive crime in England and Wales.

- The first approach was a police force area-level comparison of Addicts Index and police recorded crime data from 1981 to 1996, through the crime turning point. This showed that different types of theft generally peaked together *within* an area. But the timing and size of these peaks varied *across* areas and was highly correlated with heroin use. Fixed effects regression analysis suggested that about 40% of the national rise in the highest-volume crime types (burglary and vehicle crime), from 1981 to the peak, can be attributed to rises in the number of heroin users.

- A second approach was to model the number of heroin/crack users and their offending over time. Exploratory model results found that heroin/crack use could account for at least half of the rise in acquisitive crime in England and Wales to 1995 and between a quarter and a third of the fall to 2012, as the epidemic cohort aged, received treatment, quit illicit drug use or died.

- Model results also suggested that the epidemic still affects acquisitive crime today. In the recent recession, crime in England and Wales continued to fall, which correlates with a slowly shrinking heroin/crack user population but not with economic factors. Projecting forwards, further downward pressure on crime, of a lessening degree, might be expected as the heroin/crack cohort continues to age and get treatment.

- The evidence presented shows that detecting and preventing future drug epidemics is paramount, and this requires local as well as national monitoring. Evidence also suggests that, for crime reduction, it is crucial to maintain a focus on heroin/crack, despite the higher prevalence of other illicit drugs like cannabis, powder cocaine and ecstasy, and the emergence of new psychoactive substances. Specifically, it remains important to identify the minority of heroin/crack users who commit large volumes of crime during addiction periods. If that can be done, and those periods of addiction and offending shortened or prevented, the potential for further reductions in crime remains significant. However, many of these individuals will have been using heroin/crack intermittently for a decade or more though and will have tried most current forms of treatment, so innovative approaches may be needed.

- Finally, although this paper has drawn together a wide body of evidence, the `hidden' nature of the group being studied – heroin/crack users – means robust data remain sparse. Hence, results should be treated cautiously and hopefully built upon in the future.

Chapter 1: Introduction and methodology

The long-run decline in crime in England and Wales has prompted a variety of analyses and research, but a defining explanation remains elusive (for a review, see Farrell *et al.,* 2010). Improving the understanding of past crime trends is more than just an academic exercise. It has the potential to add considerable value to policy approaches to crime reduction. Only by understanding the factors that have driven crime in the past can these factors be correctly prioritised in the future.

The particular focus of this study is the relationship between illicit drug use and crime. It examines the potential crime impact of the marked changes in the number of users of opiates (primarily heroin) and crack-cocaine (hereafter referred to as ‘crack’) that have occurred since 1980. This is because, despite a wide literature on the link between opiate/crack use and crime, few, if any, studies have attempted to quantify its effect on *overall* crime trends.

This study is a first attempt to marshal all the available evidence on this question. It concludes with some quantitative estimates of the proportion of the rise and fall in crime that might be attributable to changes in the number of opiate/crack users (OCUs), but these should be seen as exploratory rather than definitive.

Specifically, the study has the following aims.

- To describe the nature of heroin epidemics, specifically the spread of opiate/crack use in England and Wales since 1980.

- To examine the relationship between changes in the levels of acquisitive crime and opiate/crack use, focusing particularly on how crime changes in police force areas map onto changes in the OCU population.

- To model changes in the OCU population since 1980, and if possible, assess the contribution that changes in the number of OCUs has made to overall acquisitive crime trends.

There are two versions of this paper: a short version and this longer, more technical version. This version provides more methodological details, but also more background material on crime trends and further assessment of explanations for the rise and fall.

Methodology

One of the challenges of analysing the relationship between trends in illicit drug use and offending is the quality of data available. Data on the numbers and trends in OCUs are sparse due to the hidden nature of this population. This creates two significant and related problems.

- Because the most chaotic users tend not to be captured by national-level surveys, much of what is known about OCUs comes from data on treatment or the criminal justice system. As many researchers have pointed out (see, for example, Stevens, 2007) this almost certainly creates a biased sample. As the evidence presented throughout this paper suggests, many OCUs do not get arrested, and many quit without treatment, hence relying on these sub-populations risks delivering a sample that is more crime-prone than the true population.

- The second problem relates to longitudinal research into illicit drug use. For opiate/crack use, virtually all longitudinal studies are retrospective, due to the fact that only a very small proportion of the general population become OCUs. So prospective cohorts, like, for example, the Cambridge Delinquency Study (Farrington *et al*, 2006), often fail to pick up enough individuals who go on to become OCUs for any meaningful conclusions to be drawn. But retrospective studies, of the kind drawn upon in this study, may be affected by selection bias if the more recalcitrant users are those easiest to identify in retrospect.

Data on offending are also problematic. Offending rates and trends obtained from surveys may suffer from recall bias and almost invariably involve extrapolation over time. Frustratingly, these two issues balance each other, so researchers can only make one better by making the other worse. A shorter reference period in which to capture offending levels (say, the past four weeks) will improve the chances of accurate recall, but will invariably mean a greater degree of extrapolation. It will require multiplying up by a factor of 13 to get an annual figure, which increases the chance that the measured 4-week period may not be representative. But offending rates and trends obtained from official data, like police recorded crime, provide only a partial picture, as not all crime is reported and an even smaller proportion results in arrest or conviction.

The overall approach in this report has been to exploit the full range of international research evidence and UK datasets, since no single dataset and no single methodology can definitively answer the research questions posed. A key feature of the analysis has therefore been *triangulation*. Conclusions have, where possible, been tested against a variety of alternative approaches and data sources. A second feature of the analysis is the focus on examining *regional* trends in crime and OCU populations, rather than focusing solely on the national level. Finally, the study also attempts to assess when and how opiate/crack use might have *interacted* with other drivers of crime.

For the most part, the paper uses three types of methodology.

1) **Reviews of the existing research literature**: For the chapters on general crime trends, theories of crime trends, the history of the heroin epidemic and the possible causal relationship between crime and opiate/crack use (Chapters 2 to 4), the existing UK and international research evidence was reviewed and synthesised. In other words, the focus was on summarising and categorising

existing studies rather than conducting new analysis. Although the principles of systematic searching were adhered to, the review does not meet the standards set in formal rapid evidence assessments or systematic reviews. This partly reflected the diverse nature of the subject matter covered. Hence the researchers merely seek to be transparent about the process and to encourage others to add evidence that may have been missed or misrepresented.

2) **Statistical analysis of recorded crime and the Addicts Index trends**: Chapter 5 contains a section of new statistical analysis aiming to test whether regional trends in opiate/crack use help to explain the geographic variation in crime that was seen through the 1980s and 1990s. It uses the following datasets:

   - annual police force area level recorded crime volumes for burglary and vehicle crime from 1980/81 to 1997/98;

   - annual police force area level Addicts Index data for volumes of new and total heroin users from 1977 to 1996;

   - annual police force area level claimant count volumes (a proxy for unemployment) from NOMIS for the period 1983 to 1998.

   This panel dataset was used to conduct a series of statistical, parametric tests, ranging from standard bivariate correlations and scatter-plots, to multivariate fixed effects regression analyses. The data sources were selected as the best available, but they have limitations. For crime, recorded crime data were used because they are the only source available at the local level. Victimisation surveys like the Crime Survey for England and Wales (CSEW), formerly the British Crime Survey, are generally better measures of trends because they are unaffected by reporting/recording changes. But the CSEW sample sizes were too small throughout the 1980s and early 1990s to conduct meaningful analysis at the sub-national level. To try to mitigate the issues with the recorded crime data, the analysis was restricted to the period before 1998 (recorded crime was affected by recording practice changes from 1998 until around 2004).[2] Only trends in burglary and vehicle crime were looked at for two reasons.

   - It is generally acknowledged that these are the most reliably recorded volume crime types (Chapter 2 shows that for these crimes there is a high degree of similarity between the trends in police recorded crime and those from the CSEW).

[2] The City of London was also excluded from the analysis as it generally has much smaller counts of crime than the other police force areas, which can skew results.

- These crimes comprised more than one-half of all offences recorded by the police at that time, so were the ones driving the overall trend.[3]

For trends in heroin/crack use, the Addicts Index was used as this is the only data source for OCUs available at police force level through the period. It is not a perfect measure as OCUs tended to be notified to the Index only once they sought medical attention. Evidence suggests that this usually occurs several years after the onset of regular use, and some users may never seek treatment (Millar *et al.*, 2001). Hence the data probably lag and under-count reality. Various methods are used to mitigate this issue, including specific modelling of lags. In addition, there is a break in the total heroin users series after 1986, when a slightly different methodology was employed - see Appendix 8. For the panel analysis then we only use this data from 1987. The dataset was discontinued after 1996.
For unemployment, claimant count data was used as a proxy as it is available at the local authority level from NOMIS from 1983. Local authorities are smaller than police force areas but the data was aggregated and mapped on to police force areas. The data provides the number of people claiming Jobseekers Allowance (JSA) and National Insurance credits at Jobcentre Plus local offices.

3) **Modelling offending by the OCU population**: In addition to examining the relationship between OCUs and crime at the aggregate level (a kind of top-down approach), the study also employs a bottom-up method in Chapter 6. This uses evidence from studies measuring the self-reported offending of specific cohorts of OCUs and then extrapolates the results – taking care to avoid potential bias – to the entire OCU population. By also modelling the trend in the OCU population over time, the analysis leads to estimates for the amount of *additional* acquisitive crime generated by the epidemic, and hence the degree to which opiate/crack use might have contributed to the rise and fall in crime.

   Unlike Chapter 4, which uses recorded crime, this chapter uses self-reported offending data. This was partly to provide triangulation and partly because studies have shown that annual offending rates generated from criminal justice system data are likely to under-represent the degree to which total offending is skewed towards a small number of the most prolific offenders (Farrington *et al*., 2006).

   Modelling of this type inevitably involves numerous simplifications and assumptions. These are listed in full in the longer version of this paper, but most relate to the weaknesses in the underlying data

[3] Specifically, 57% of the rise in total recorded crime from 1980 to 1992 was due to the increase in burglary and theft of/from vehicle.

explained above. For that reason, the results of this modelling process should be viewed as exploratory.

Structure of the paper

The paper is divided into six chapters. Chapter 2 looks at what is known about crime trends in England and Wales from 1980 to the present, including a brief examination of their similarity to trends in other nations. The focus is mainly on acquisitive crime because this has the strongest link to opiate/crack use. An assessment of some of the other theories that have been offered to explain these trends is included.

Chapter 3 pieces together the story of the heroin epidemic in England and Wales with a particular emphasis on the variation in the timing at which the epidemic affected different areas, so that variation in the crime data can be considered against this. Chapter 4 summarises the existing research evidence on whether there is a causal link between opiate/crack use and crime.

Chapter 5 examines the relationship between trends in opiate/crack use and crime at the local, national and international level. The chapter is part descriptive, examining whether the epidemic narrative helps to explain some of the variation in crime trends described in Chapter 2. But it also contains statistical analysis in which these explanations are tested more robustly.

Chapter 6 provides a brief description of the modelling of the OCU population and estimates the potential impact of the heroin epidemic on CSEW acquisitive crime trends.

Finally there is a brief conclusion, summarising the findings and drawing out several policy implications.

Chapter 2: An overview of crime trends and explanations of the crime drop

Overview of Crime Trends

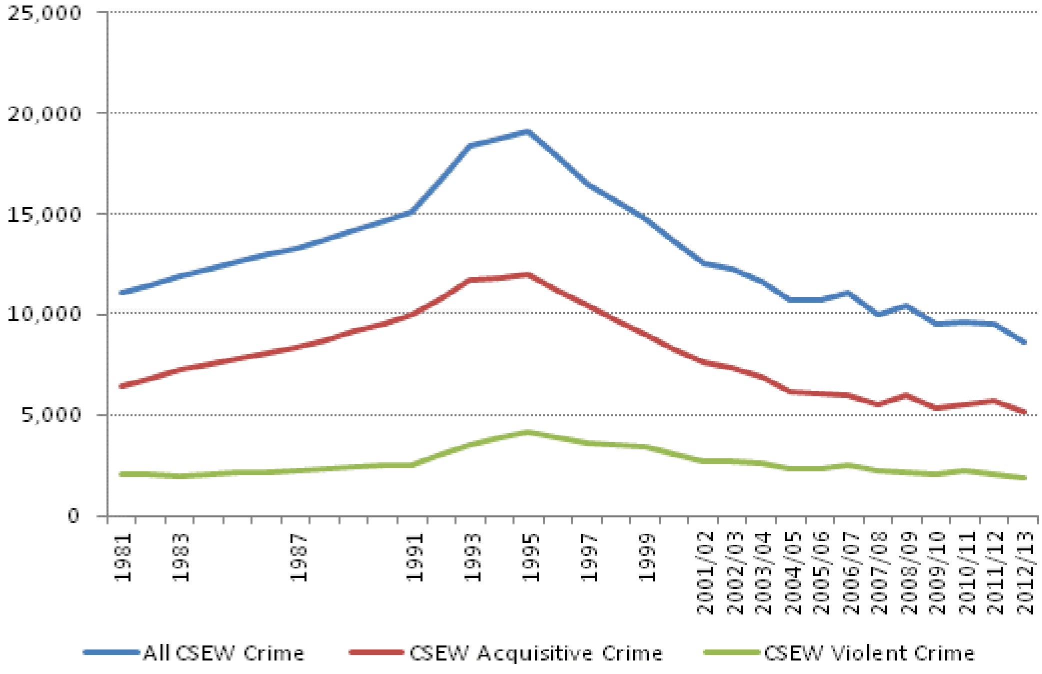
National-level trends

The first section of this chapter provides an overview of the data on longer term crime trends in England and Wales. It draws out some key facts against which to judge factors that might explain the rise and fall in crime.

There are two primary measures of crime in England and Wales: police recorded crime (PRC); and the Crime Survey for England and Wales (CSEW), formerly the British Crime Survey.

The CSEW, which asks a large sample of the population about their crime victimisation experiences,[4] shows a rise in crime through the 1980s, a sharp increase in the early 1990s and a sustained fall from 1995. The fall has continued to the present day (2013), albeit at a slightly decreasing rate, see Figure 1.

Figure 1: Crime incidents, 1981 to 2012/13



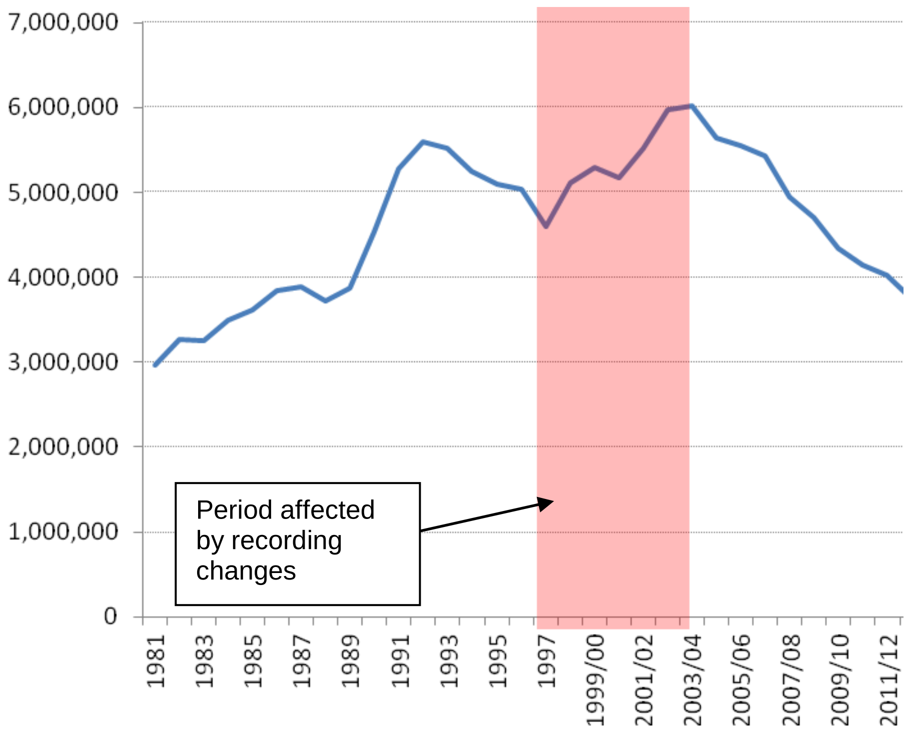
[4] The BCS/CSEW therefore only includes crimes against individuals and households. It does not include crimes against commercial targets or crimes in which there is no obvious victim, like drug offences. In addition, the main survey count does not include offences against any individuals aged under 16 (though separate questions looking at crime experienced by 10-16 year-olds have been added in recent years), and also excludes crimes against people living in institutions, communal establishments or on the streets. Also, though generally judged the best measure of overall long-term trends, the CSEW is less reliable for trends in serious crimes, like serious violence. This is because few incidences occur nationally, so sample numbers are small. For the most part though, this paper is concerned with high-volume acquisitive crimes, so the CSEW should be a reliable guide to trends.

Source: Crime Survey for England and Wales 2012/13

Breaking the CSEW trend down into violence and acquisitive offences shows that both peak in the mid-90s and that there are around three acquisitive crimes for every one violent crime. The ratio climbed to around 4:1 in the early 1990s but has been between 2.5:1 and 3:1 since 1995. Hence, acquisitive crime has mostly been the driving force in overall crime trends since 1981.

PRC describes crime that is reported to and recorded by the police. Major changes in police recording practice occurred in 1998 and 2002.[5] These resulted in the improved recording of some crimes, particularly minor violence. It is almost certainly the reason that PRC peaks in 2003/04 (see Figure 2). Removing the period during which the recording changes would have altered the underlying trend (1998 to 2004), PRC reveals a similar picture to the CSEW. It rises gradually in the 1980s, sharply in the early 1990s and then has a prolonged fall.

Figure 2: Total offences, 1981 to 2011/12



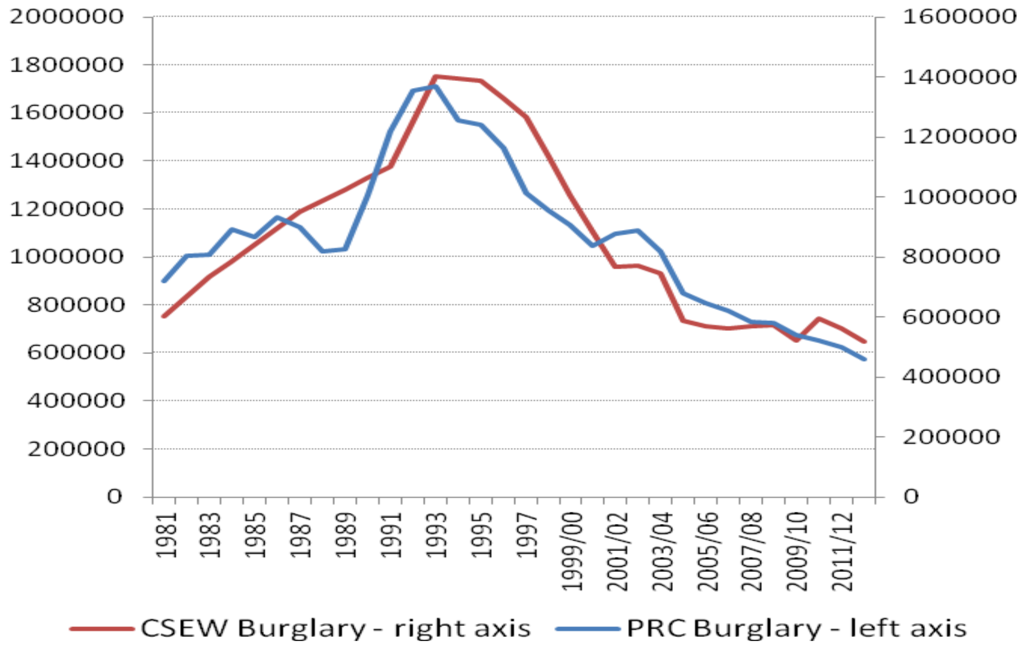
Source: ONS, police recorded crime

A good indication that the 2003/4 'peak' is caused by the recording changes is given by a comparison of CSEW and recorded crime trends for high-volume acquisitive crimes like burglary and vehicle crime. These crime types are well reported and recorded and are unlikely to have been markedly affected by the recording changes. As the charts below show, these crimes have similar trends on CSEW and PRC and have a single early 90s peak. So, for the

[5] For full details of these see Berman, 2008.

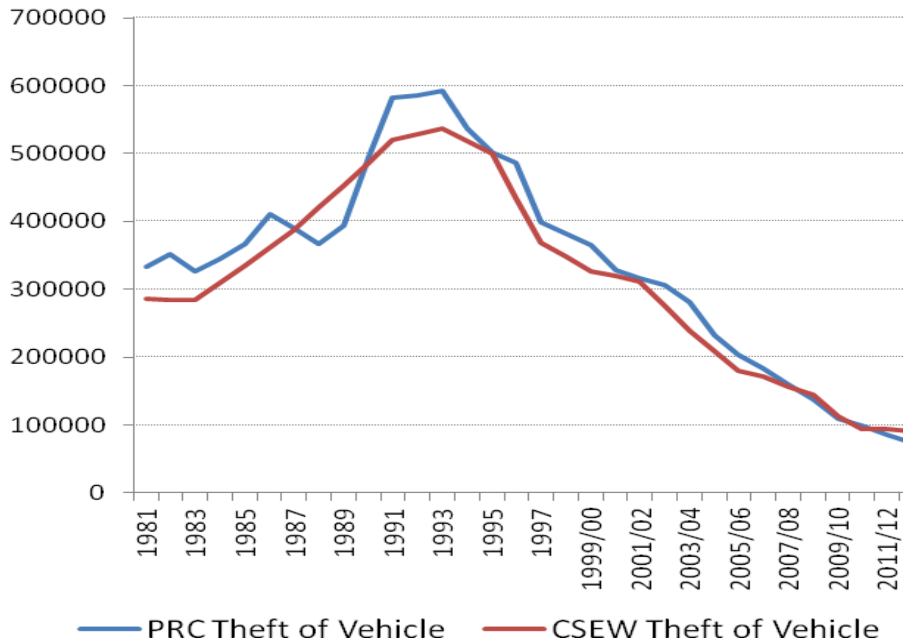
crimes that really drove the overall trend (burglary and vehicle crime constituted just over 50% of all recorded crime at the peak), there can be a degree of confidence that the national mid-90s turning point and the rise and fall either side, are genuine and worthy of explanation:

Figure 3: Comparison of burglary trends, PRC and CSEW[6]



Source: ONS, Crime in England & Wales 2012/13

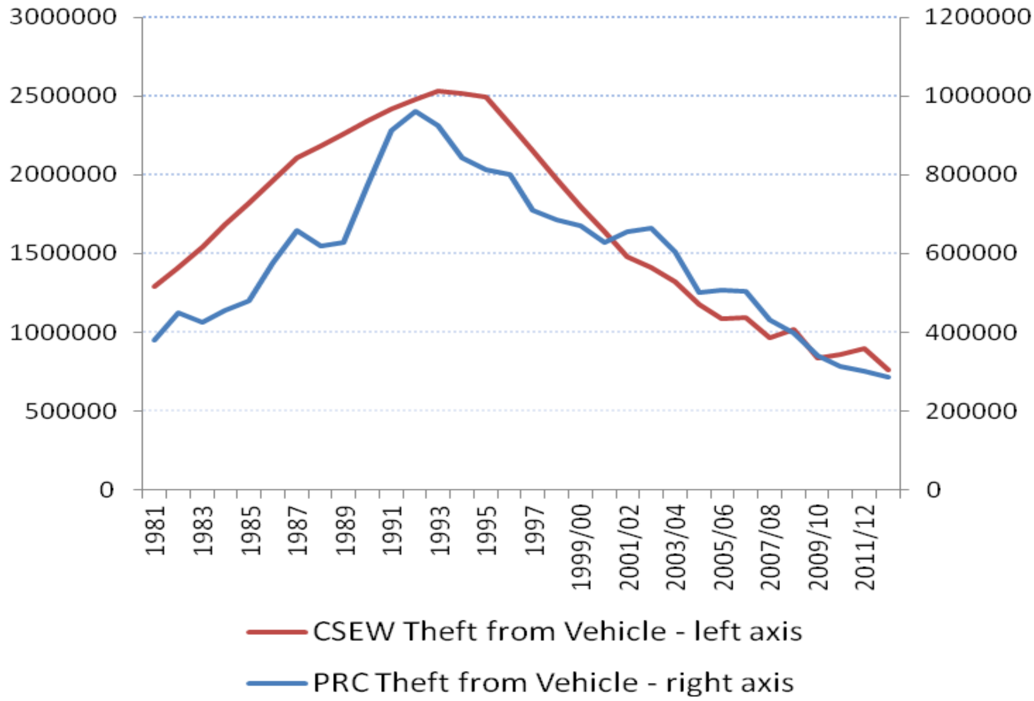
Figure 4: Comparison of `theft of vehicle' trends, PRC and CSEW



[6] On the burglary chart, it is noticeable that the CSEW burglary peak appears to be slightly later than for PRC. One explanation for this is that CSEW interviews are done over a 12 month period with victims asked about experiences in the last year, so some incidents captured will actually have taken place almost two years ago. In other words, it would be expected to lag PRC slightly.

Source: ONS, Crime in England & Wales 2012/13

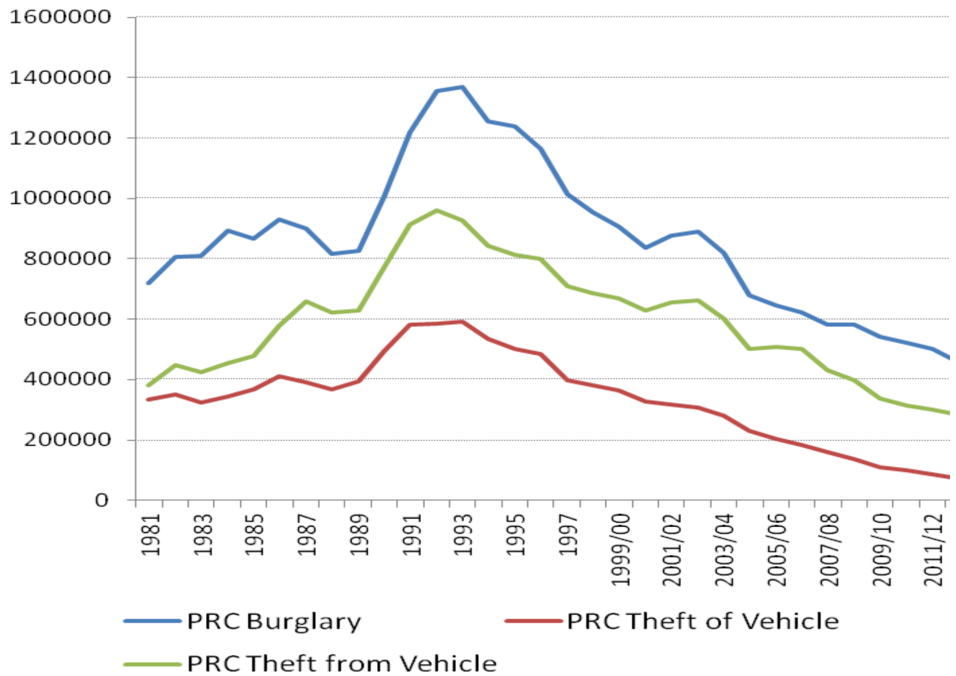
Figure 5: Comparison of `theft from vehicle' trends, PRC and CSEW



Source: ONS, Crime in England & Wales 2012/13

These graphs also suggest that the crime rise, turning point and fall have been very consistent across high-volume acquisitive offences. This is shown even more clearly on the chart below:

Figure 6: Comparison of trends in three high-volume theft crimes

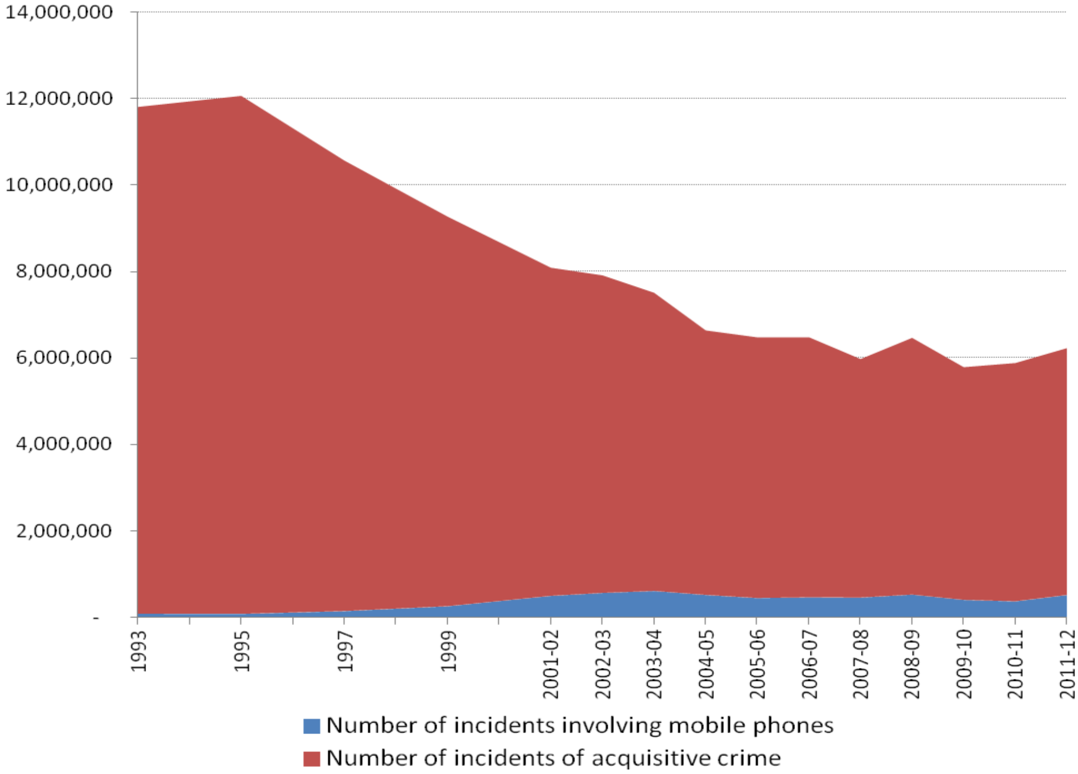


Source: ONS, Crime in England & Wales 2012/13

Figure 6 also shows a slight fall in PRC for these acquisitive crime types from around 1987 to 1989. The CSEW was not carried out between 1987 and 1991 so would not register this, but the consistency with which it appears in the PRC trends suggest that it was a genuine 'lull' in the rise in crime.

Not all crime types followed this pattern. Vandalism (as measured by the CSEW) had a more gradual rise and fall, though it still peaked in the mid-1990s. And within acquisitive crime, the items stolen shifted. The introduction and spread of mobile phones prompted an increase in thefts of these items through the late 1990s and early 2000s, just as the desirability (and re-sale value) of other previously stolen goods like car radios and video recorders declined. Despite these variations though, the overall *propensity* for acquisitive crime declined hugely from the mid 1990s, as Figure 7 shows[7]:

Figure 7: The fall in CSEW acquisitive crime



Source: ONS, CSEW.

In fact, the decline in acquisitive crime was probably even starker than Figure 7 suggests as it does not include crimes against businesses. Some of these, like shoplifting, are extremely high-volume offences. The Commercial

[7] It is also worth noting that, even correcting for inflation, smartphones are probably worth more to thieves today than video recorders and car stereos were in the 1980s and 1990s when these were the most stolen items. Hence, it seems unlikely that the crime fall is entirely due to changes in the value of steal-able goods. In addition, given that smartphones are now ubiquitous and carried on people's person or in bags, they are also arguably more accessible than previous stolen items: no house-breaking or vehicle entering is required. Hence, theories of the crime drop that emphasise ease of opportunity might predict higher crime levels today. This evidence might therefore suggest that, irrespective of opportunity, there must have been a considerable drop in the propensity for theft crimes.

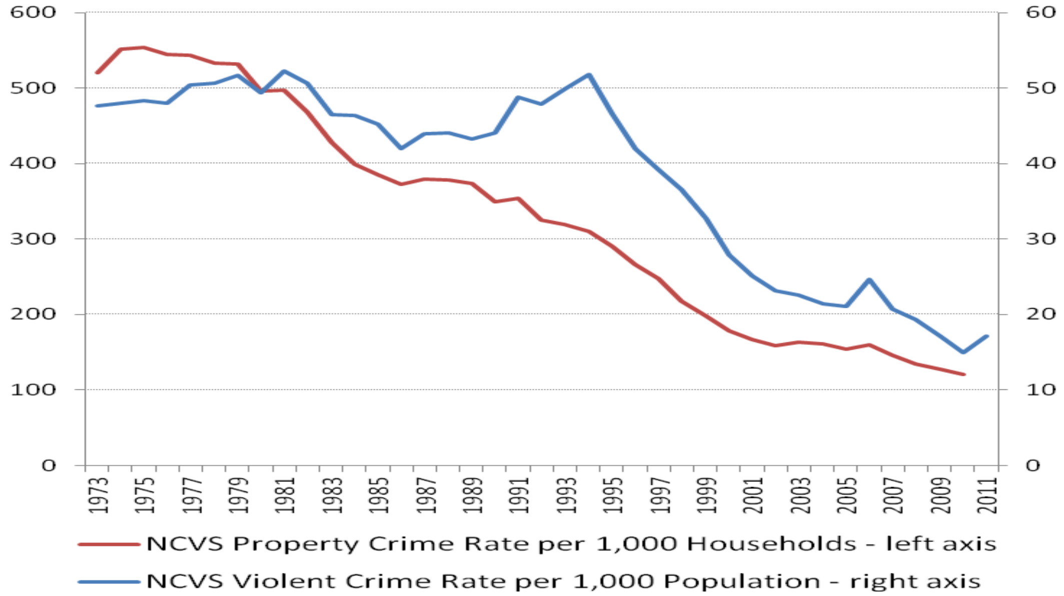
Victimisation Survey records a 64% fall in shoplifting between 2002 and 2012, the equivalent of *14 million* fewer offences.[8] (ONS, 2013_2)

Another important fact about the national-level trend in England and Wales is that it did not alter during the recent recession. Though the falls in Gross Domestic Product were the worst in nearly sixty years (GDP fell around 6% from peak in early 2008 to trough in the second quarter of 2009) crime continued to fall at about the same rate in the five years after the recession as the five years before. Clearly, this is another fact that requires explanation.

International trends

Commentators have noted that the trend in England and Wales has been similar to that in other western nations. This is true to an extent but there are also important differences. According to the National Crime Victimization Survey (NCVS), the equivalent of the CSEW in the US, the rate of property crime, which is mostly theft offences, peaked in the 1970s in the US, far earlier than it did in England and Wales, see Figure 8:[9]

Figure 8: Crime trends in the United States, NCVS



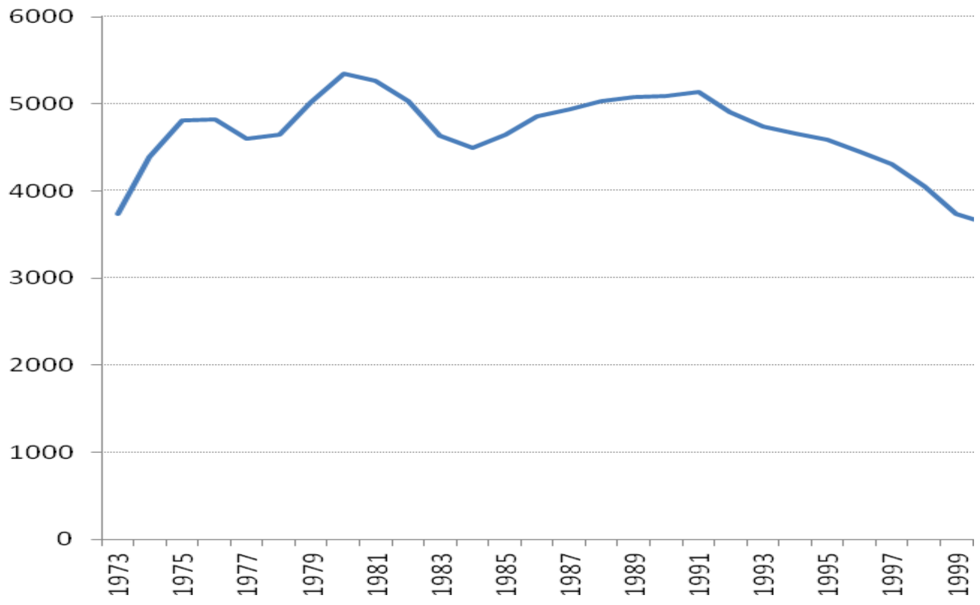
Source: National Crime Victimization Survey, Bureau of Justice.

This is reinforced by the US rate for *police recorded* property crime. It shows a peak around 1980, which is also far earlier than in England and Wales, see Figure 9.

[8] This is more than the total number of crimes recorded by the CSEW and police recorded crime, for the most recent year.

[9] The NCVS property crime peak would be slightly later if measured in volumes rather than rates, probably around 1979 to 1981 by this paper's calculations; and that the property crime peak in US *recorded* crime is 1991. But, even amongst the recorded crime types, the most reliably recorded offences like burglary show an earlier peak (1981). So, whichever measure is used, the data suggest that the US had a far earlier peak in acquisitive crime than England and Wales.

Figure 9: Crime trends in the United States, property crimes per 100,000 population



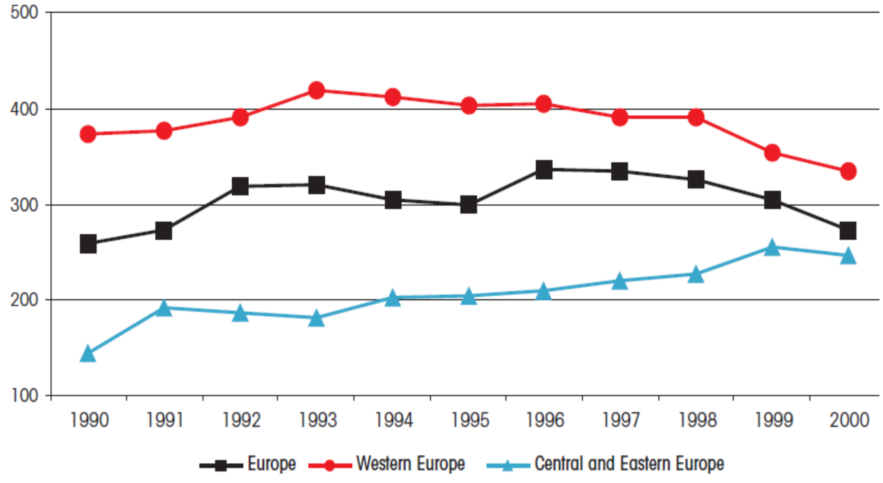
Source: Federal Bureau of Investigation, Uniform Crime Reports

In other nations, trends are more difficult to discern, as victimisation surveys have been carried out less frequently, or not at all. But using all available evidence, it would appear that Canadian crime trends were similar to those in the US (Zimring, 2007). Property crime rose markedly to 1981, but was then fairly stable until 1991 when it started a sustained fall, with violence following a year later.[10] Like Canada and the US, Scotland and the Republic of Ireland also appear to have had earlier crime peaks than in England and Wales. Recorded crime in the Republic of Ireland[11] shows a 1984 peak, while recorded crime in Scotland started falling from 1991.

In Australia though, property crime didn't peak until about 2001 and violence not until about 2007. In mainland Europe, Aebi (2004) found that the average property crime peak amongst Western European nations was 1993, in line with England and Wales. But the average peak for Central and Eastern European nations was later, see Figure 10 below:

[10] The one exception to this is vehicle theft, which has a peak in 1996 but only starts falling significantly in about 2006.
[11] The 1984 peak in the Republic of Ireland refers to total recorded crime involving both indictable and non-indictable offences – http://www.crimecouncil.gov.ie/statistics_cri_crime.html. The trend in indictable offences also shows a 1983/84 peak but reaches its highest level in 2002, although this is likely to be an artefact of recording practice changes.

Figure 10: Median rates of theft per 100,000 population from 1990 to 2000 in 19 European countries according to police statistics



Source: Aebi (2004).

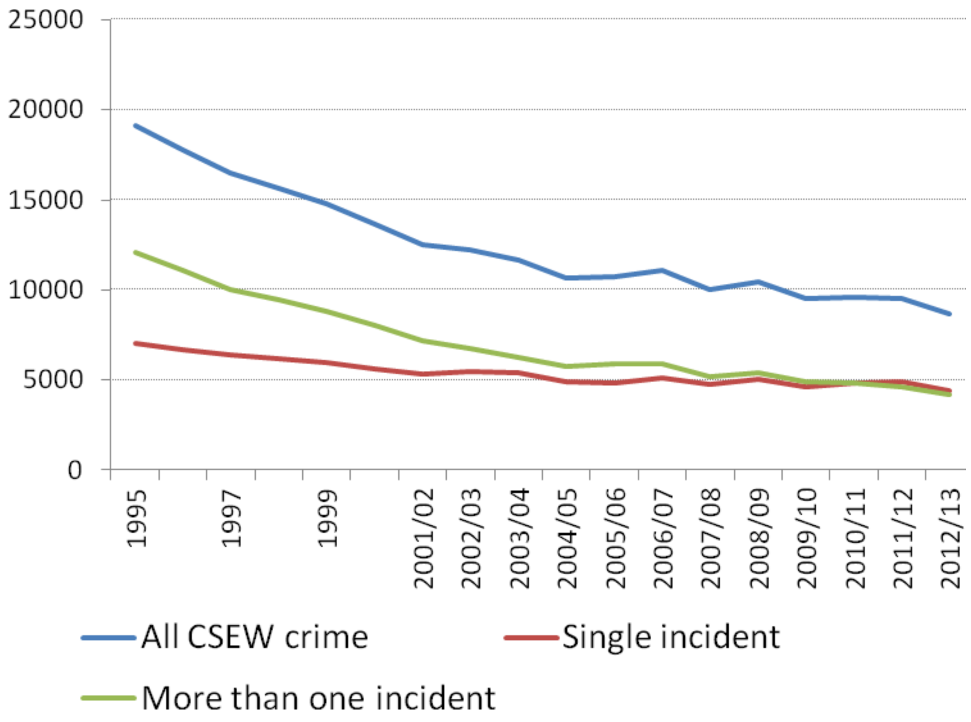
Overall, it is clear that there are both similarities and differences between crime trends in England and Wales and those in other nations, and any explanation of crime trends needs to contend with these.

Other facts about the national level trend

There are a few other facts about the national-level trend that are worth mentioning briefly. The first is that the rise and fall in crime in England and Wales seems to have been due largely to a rise and fall in repeat victimisation. As with offenders, studies show that victimisation is highly skewed (ONS, 2013c). A comparatively small number of victims experience disproportionately high levels of crime.[12] Studies show that this disproportionately rose in line with crime to the mid 1990s peak and then has fallen since (ibid.). In other words, the crime trend has been driven mostly by changes in the number of offences experienced by the most-victimised minority, rather than in changes to those only victimised once in a given year, as Figure 11 shows:

[12] This is true both in terms of people, and for offences like burglary in terms of households or business properties.

Figure 11: Trends in the number of total incidents (in 000s) of crime experienced by single and repeat victimisation, 1995 to 2012/13 CSEW



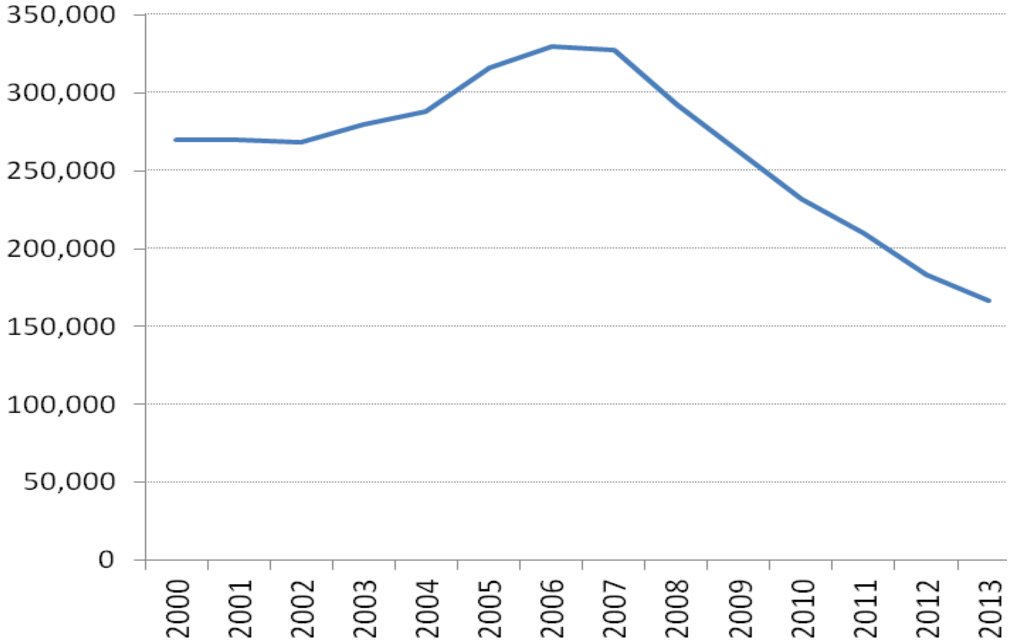
Source: ONS, 2013c

Linked to this perhaps, are two other, more tentative, observations on the changing nature of offending. Data suggest that the crime decline has been most prominent in younger age groups and that the number of first-time offenders has reduced over time. Unfortunately, data does not allow certainty in these conclusions for two reasons:

i) Only a proportion of offences result in an offender being cautioned or found guilty, and it is only at this stage that age and previous offending history (or lack of it) can be determined.
ii) There has been a trend over the last 35 years at least towards finding more diversionary punishments for younger offenders, particularly those aged 10-17.

The second point is certainly part of the reason that there are fewer first-time offenders in the statistics now than in 2000, see Figure 12 below.

Figure 12: First offences committed by offenders of all ages and resulting in a reprimand, warning, caution or conviction, England and Wales, 2000 - 2013[13]



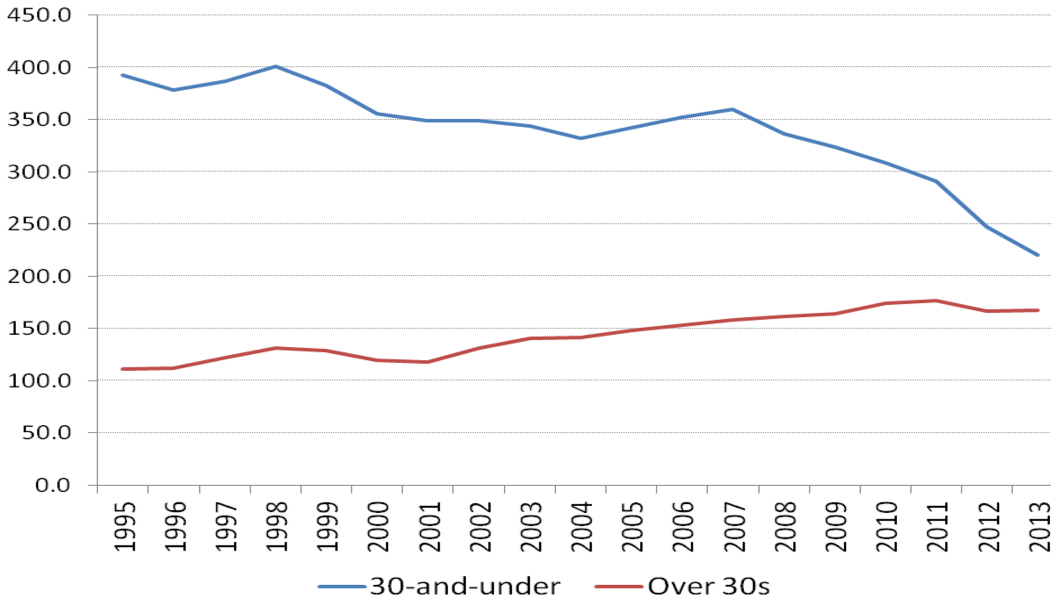
Source: Data supplied by Ministry of Justice (MOJ)

The chart shows that the trend in numbers of first-time offenders decreased very slightly between 2000 and 2002. It then rose to around 2006/07 before falling sharply through to 2013. The reason for the rise mid-series was almost certainly the introduction of the Offences Brought to Justice (OBTJ) target in 2001. This is likely to have driven up the numbers of certain offences, like drug offences, which by their very nature have a high detection rate and which mostly involved cannabis possession by younger, first-time offenders. Since the target was removed in 2008, first-time entrants have fallen sharply. Even so, the 2013 level is almost 40% lower than that in 2000.

Though the caveats mentioned above also apply, the trend away from younger offenders is even clearer. As Figure 13 shows, the crime decline has been accompanied by a very clear divergence between offenders aged 30-and-under and those aged over 30:

[13] Note that these figures do not include first time offenders that receive a community resolution like restorative justice. It is difficult to know exactly how much difference this might make to the trend. Restorative justice is likely to be an approach that is used for first-time offenders and has almost certainly increased in recent years, but the exact magnitudes are hard to determine. Our best estimate is that this effect would not be enough to offset the overall decline in first-time entrants.

Figure 13: Number of persons (in 000s) found guilty or cautioned for indictable offences, by age.[14]



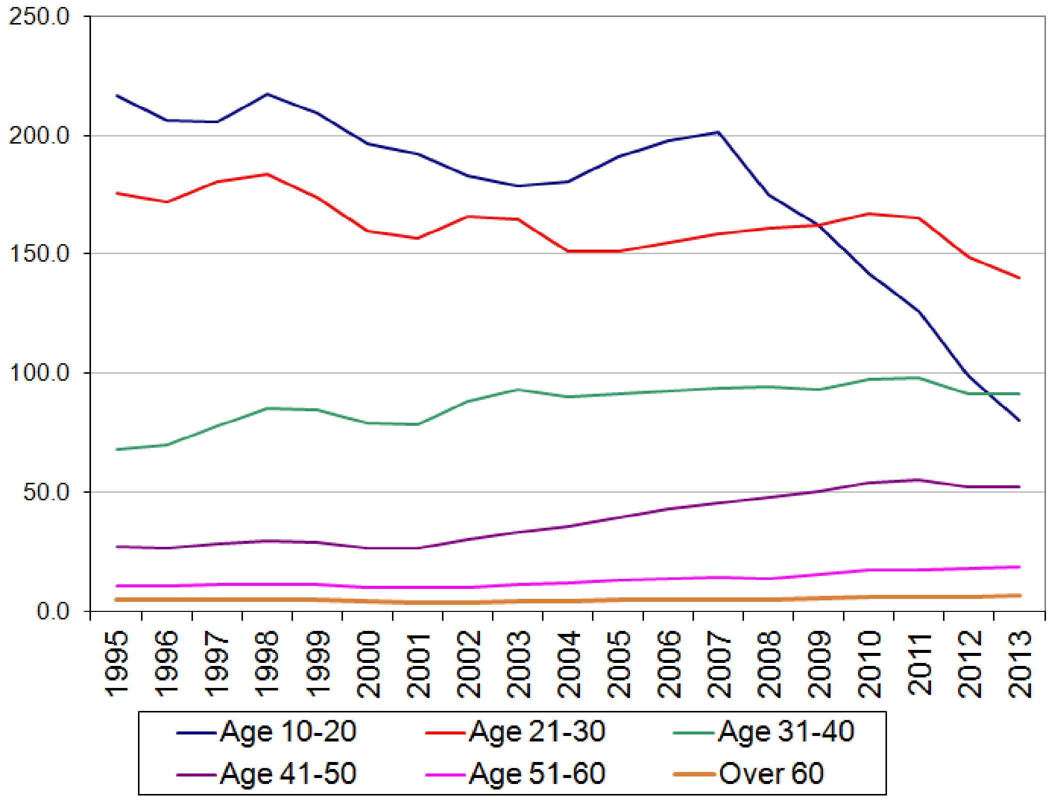
Source: Data supplied by Ministry of Justice (MOJ)

Figure 13 suggests that if current trends continue, a greater proportion of persons found guilty or cautioned for indictable offences will soon be over 30 rather than 30-or-under. Whether this can be wholly attributed to the mentioned criminal justice system changes is difficult to know definitively. But breaking the trends down does suggest there may be other factors involved.

(Figure 14 on next page.)

[14] The fact that these data series use indictable offences, mean that two further caveats are necessary. Firstly, from at least 2000, a greater number of some offences (like common assault), which in the past have tended to be committed more by the younger age group, have moved from indictable offences into summary offences. Secondly, the introduction of cannabis warnings and penalty notices for disorder which are not captured in the chart above, but which have disproportionately been given to those under 30

Figure 14: Number of persons (in 000s) found guilty or cautioned for indictable offences, by age at time of offence



Source: Data supplied by Ministry of Justice (MOJ)

There are two points to make about Figure 14, one obvious; one more subtle. The obvious point is the sharp decline in the number of proven offenders aged 10-20. This group almost exactly halved between 2007 and 2012, and have gone from being clearly the most prolific group to a position that is about a third lower than the 21-30s and almost in line with the 31-40s. Clearly, the sharpness of the trend suggests some sort of policy change (recall that the OBTJ target was removed in 2008), but it is also clear that looking from 1995 to 2012, the general trend is markedly downwards. Whether this is purely an artefact of policy changes or indicates that younger people are genuinely becoming less likely to commit crime is impossible to say from these data. But the fact that young people also seem to be less likely to commit other kinds of risky behaviour like drinking, smoking, taking drugs, and so on, perhaps suggests that at least part of the trend is genuine.

The more subtle point about Figure 14 is that there are some tentative signs of a `cohort effect' among the older age groups. While the younger age groups have seen obvious falls, all the groups aged 31 and over have seen rises over the period. Crucially though, *these increases occur at different times*. Proven offences by those aged 30-40 rose most markedly from the mid-1990s to around 2003, but were then fairly stable to 2012. The number of proven offenders aged 41-50 was fairly flat to 2001, but then it roughly doubled between 2001 and 2010. The over-50s have also seen rises recently and are the only group to continue to see an increase in the most recent year. Taken together, these trends could suggest the presence of a high-crime cohort working its way through the age categories, especially as the move towards more diversionary punishments for younger offenders would have been less likely to bias trends in older offenders. However, any indication of a cohort effect currently remains tentative due to the limitations of the data. As such, this offers a potentially fruitful area for further research.

Local Trends

Like the international trends, analysis of crime *within* England and Wales reveals variation in the magnitude and timing of the rise and fall in crime. There are 44 police force areas in England and Wales[15] and whilst trends in all of them show an overall rise and fall in acquisitive crime, they do so at different times and to different degrees.

Virtually all forces had large increases in acquisitive crime from 1980 to 1993 and, as nationally, the rise was particularly concentrated for most areas at the beginning of the 1990s. This is shown for police recorded burglary in Table 1.[16] Taking a single example, South Yorkshire had a 235% rise in burglary from 1980/81 to 1993/94, but the vast majority of this rise (81%) occurred in the 4-year period from 1989/90.

Table 1: Table showing increases in police recorded burglary, by police force area, 1980/81 to 1993/94

	Burglary volume in 1980/81	Burglary volume in 1989/90	Burglary volume in 1993/94	Total burglary increase: 1980/81 to 1993/94 (volume)	Total burglary increase: 1980/81 to 1993/94 (% change)	Percentage of total rise occurring between 1989/90 and 1993/94
Avon and Somerset	11,484	17,572	40,655	29,171	254%	79%
Bedfordshire	5,604	7,610	15,596	9,992	178%	80%
Cambridgeshire	4,859	6,701	15,023	10,164	209%	82%
Cheshire	8,176	10,501	22,034	13,858	170%	83%
Cleveland	8,962	14,395	18,738	9,776	109%	44%
Cumbria	4,064	6,460	10,733	6,669	164%	64%
Derbyshire	9,087	9,390	25,612	16,525	182%	98%
Devon and Cornwall	8,850	15,831	32,578	23,728	268%	71%
Dorset	4,567	5,969	9,625	5,058	111%	72%

[15] Though there are currently 44 police forces in England and Wales, we exclude British Transport Police from Table 1 as it does not cover a geographical area as such. City of London police is also excluded as it has much lower volumes of offences, so is not really comparable to the other forces.
[16] It is necessary to use PRC data at the police force area level, due to the small sample size of the CSEW at local level.

Durham	7,711	9,730	13,677	5,966	77%	66%
Dyfed-Powys	1,829	2,721	4,632	2,803	153%	68%
Essex	11,347	15,228	27,149	15,802	139%	75%
Gloucestershire	3,930	8,215	17,294	13,364	340%	68%
Greater Manchester	46,949	73,438	97,850	50,901	108%	48%
Gwent	3,967	3,838	7,091	3,124	79%	104%
Hampshire	13,297	19,578	33,066	19,769	149%	68%
Hertfordshire	5,807	6,360	13,419	7,612	131%	93%
Humberside	12,710	22,111	48,031	35,321	278%	73%
Kent	10,429	14,420	30,743	20,314	195%	80%
Lancashire	12,728	17,017	29,550	16,822	132%	75%
Leicestershire	7,162	11,552	25,210	18,048	252%	76%
Lincolnshire	3,532	6,808	13,008	9,476	268%	65%
Merseyside	34,801	36,871	33,688	-1,113	-3%	0%
Metropolitan	125,944	148,901	174,770	48,826	39%	53%
Norfolk	5,273	10,455	18,178	12,905	245%	60%
North Wales	6,107	7,387	11,990	5,883	96%	78%
North Yorkshire	5,283	8,071	16,275	10,992	208%	75%
Northamptonshire	6,048	6,392	15,944	9,896	164%	97%
Northumbria	31,068	49,585	63,007	31,939	103%	42%
Nottinghamshire	18,161	18,267	40,038	21,877	121%	100%
South Wales	20,437	25,067	38,188	17,751	87%	74%
South Yorkshire	15,641	22,514	52,396	36,755	235%	81%
Staffordshire	8,750	13,406	30,091	21,341	244%	78%
Suffolk	3,223	6,022	9,147	5,924	184%	53%
Surrey	50,84	7,193	12,815	7,731	152%	73%
Sussex	9,970	16,038	26,672	16,702	168%	64%
Thames Valley	15,227	20,280	40,345	25,118	165%	80%
Warwickshire	3,289	5,472	12,554	9,265	282%	76%
West Mercia	7,096	9,566	17,980	10,884	153%	77%
West Midlands	49,783	58,123	100,002	50,219	101%	83%
West Yorkshire	35,303	44,663	94,294	58,991	167%	84%
Wiltshire	3,780	5,301	9,118	5,338	141%	72%
Total	617,319	825,019	1,368,806	751,487	121.70%	72.36%

Source: ONS, police recorded crime, 1980/81 to 1993/94

Table 1 also reveals some variation. Whilst the majority of forces had very marked burglary increases during the period 1980/81 to 1993/94, the size of this rise (in volume and percentage terms) varies. All but two forces had rises over this period of 75% or more. The Metropolitan Police Service (MPS) was one of the exceptions. It had the second-smallest overall rise from 1980/81 to 1993/94 in percentage terms (39%), which is not simply because it has the highest overall crime volume. In volume terms its burglary rise was less than other high-volume forces like Greater Manchester Police, West Midlands and West Yorkshire.

The MPS is not the main outlier in Table 1 though. In Merseyside, burglary volumes actually fell through the period. Graphing trends in each force area reveals that the reason for Merseyside's overall burglary drop between 1980/81 and 1993/94 was simply that it had a far earlier peak. Burglary rose there until 1986/7 and then fell, so that by 1993/4 the level was lower than in 1980/81. Even amongst other forces, though the majority have peaks between 1992 and 1994, there is still a degree of variation, as Table 2 demonstrates.[17]

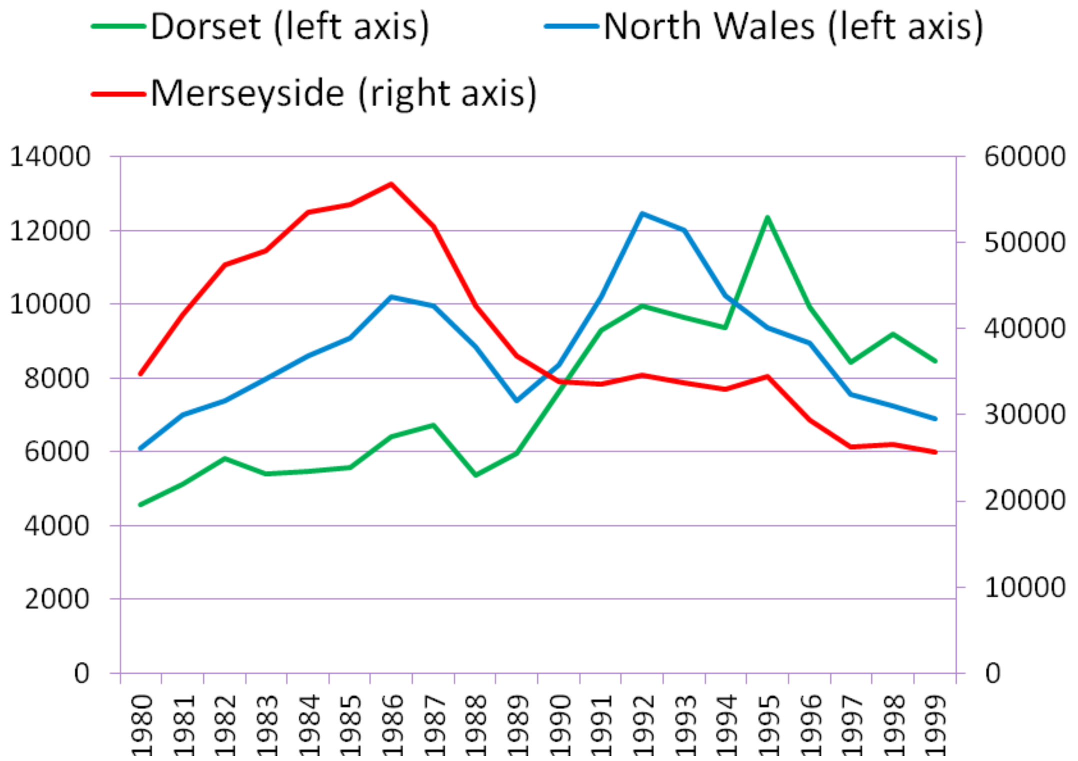
Table 2: Peak year for recorded burglary, by police force area

Police force areas	Peak year for recorded burglary
Merseyside	1986/87
Northumbria	1991/92
Metropolitan Police Service, Greater Manchester Police, Avon and Somerset, Bedfordshire, Cumbria, Dyfed-Powys, Hampshire, North Wales, South Wales, Sussex, Warwickshire, West Midlands, Wiltshire	1992/93
Cambridgeshire, Cheshire, Derbyshire, Devon and Cornwall, Essex, Gloucestershire, Hertfordshire, Humberside, Lincolnshire, Norfolk, Northamptonshire, Nottinghamshire, South Yorkshire, Staffordshire, Suffolk, Surrey, Thames Valley, West Mercia, West Yorkshire	1993/94
Leicester, North Yorkshire	1994/95
Cleveland, Dorset, Durham, Kent	1995/96
Lancashire	1996/97
Gwent	1997/98

Figure 15 illustrates the diversity of peaks with data from three forces:

[17] Appendix 1 shows that a similar variation also exists for the two types of vehicle theft.

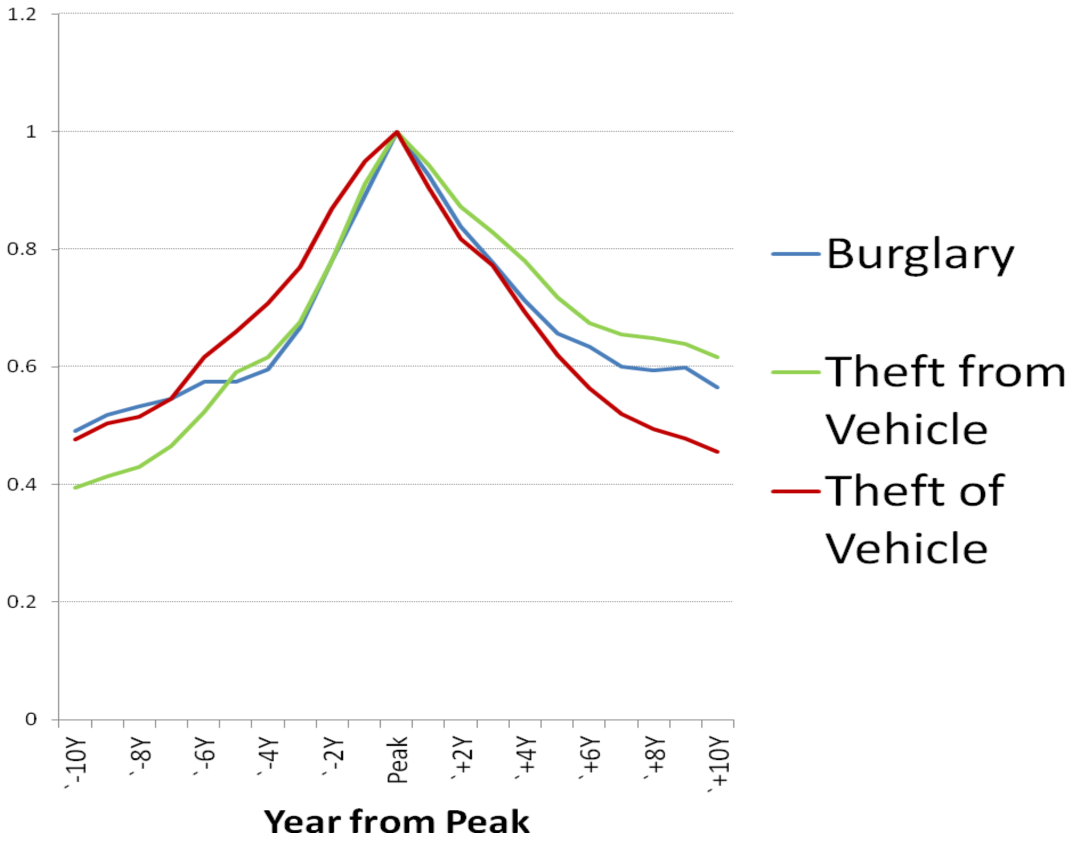
Figure 15: Police recorded burglaries in three police force areas, 1980 to 1999



Source: ONS, police recorded crime

However, *within* each police force area, as at the national level, different acquisitive crime types tended to rise and fall together. So though Table 1 focused on burglary, the increases were generally mirrored by similar rises in theft of and from vehicle. This is clearly evident in Appendix 2, which has trends for all forces. These also reveal that mostly, the rise and fall in crime either side of the turning point was not gradual but sharp. In other words, the peak in crime was not gradual, but rather, it resembled a spike in many areas. Figure 16 shows this by giving an averaged trend for each crime type, across all force areas, either side of the peak:

Figure 16: Average acquisitive crime trends for all police forces through the crime turning point, indexed to the peak year[18]



Source: ONS, police recorded crime

Figure 16 shows that volumes of burglary and theft from vehicle increased more than 65% in the four years prior to the peak in each area, which, as we've seen was a different actual year across areas. But equally, the chart shows that the vast majority of this rise was cancelled out in the four years following the peak.

The local area analysis revealed one other interesting fact about the rise and fall in crime: the percentage increases were far more pronounced in less urban forces.[19] The less urban forces tended to have almost all their crime rise focused in just a few years. Table 1 showed this, but it is more clearly illustrated in Figure 17 below. It compares the more gradual rises in burglary in the metropolitan forces with the sharper 'spikes' seen in some, more rural, forces.[20]

Figure 17: Burglary trends in selected police forces, 1980 to 2004

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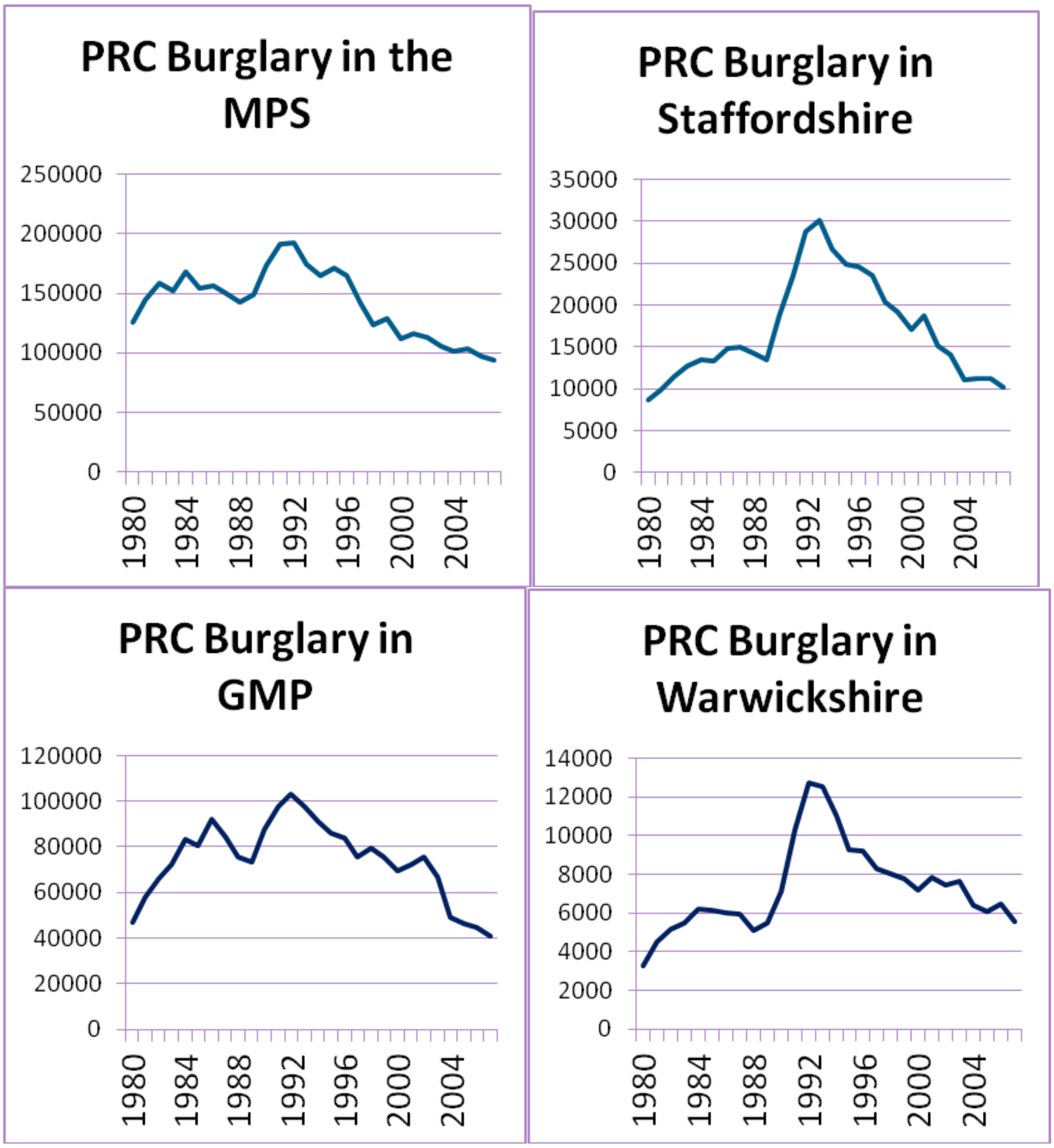
[18] City of London and British Transport Police were excluded from the analysis and the averaged pre-peak trend for the years -10Y to -7Y does not include figures for Merseyside because this took the figures into the pre-1980 period which is before we have force-level data.

[19] Note that partly this is an artefact of the data: i.e. that areas with lower crime will see bigger percentage increases simply because they have lower crime volumes to start with. But what this does show is that whatever drove up crime in England and Wales drove up crime in (virtually) all areas, and did so very severely. It was not something that was particularly focused on large, urban centres.

[20] Again, the picture is generally similar for vehicle crime – see Appendices.



Note: MPS is the Metropolitan Police Force, and GMP is the Greater Manchester Police.
Source: ONS, police recorded crime

To recap, within local areas the most voluminous acquisitive crimes tended to rise and fall simultaneously and sharply, particularly sharply in the less urban forces. Crucially however, the timing of these peaks varied between forces. In particular, Merseyside peaked much earlier than anywhere else.

We conclude this section with a list of questions, drawn from the discussion of trends, and against which we might start to explore possible drivers of crime:

<u>Questions</u>

- Why did crime in England and Wales rise steadily in the 1980s, with a slight lull from 1987-89, and then increase sharply in the early 1990s?
- Why did crime start falling equally sharply in the mid 1990s?

- Why has crime continued to fall despite the recession?

- Why did the crime decline in England and Wales start later than in some nations (like the US) but earlier than others (like Australia)?

- At the local level, why did acquisitive crime in Merseyside peak before anywhere else?

- More generally, why was there variation in the crime peaks across police force areas?

- Why was the sharpness of the mid-1990s crime `spike' particularly apparent in non-Metropolitan forces?

And more tentatively:

- Why was the decline in crime accompanied by falls in repeat victimisation and first-time offenders?

- Why has the crime decline also been accompanied by a shift from younger to older offenders?

Theories for the rise and fall in crime

Many theories have been put forward to try and explain the crime trends summarised in the previous section and it is beyond the scope of this paper to examine them all in exhaustive detail. But we include a summary here, to provide context, but also because it seems likely that ultimately a combination of these factors provide the explanation, possibility to different degrees at different times, and that at times opiate/crack use may have *interacted* with some of these other potential drivers of crime in important ways.

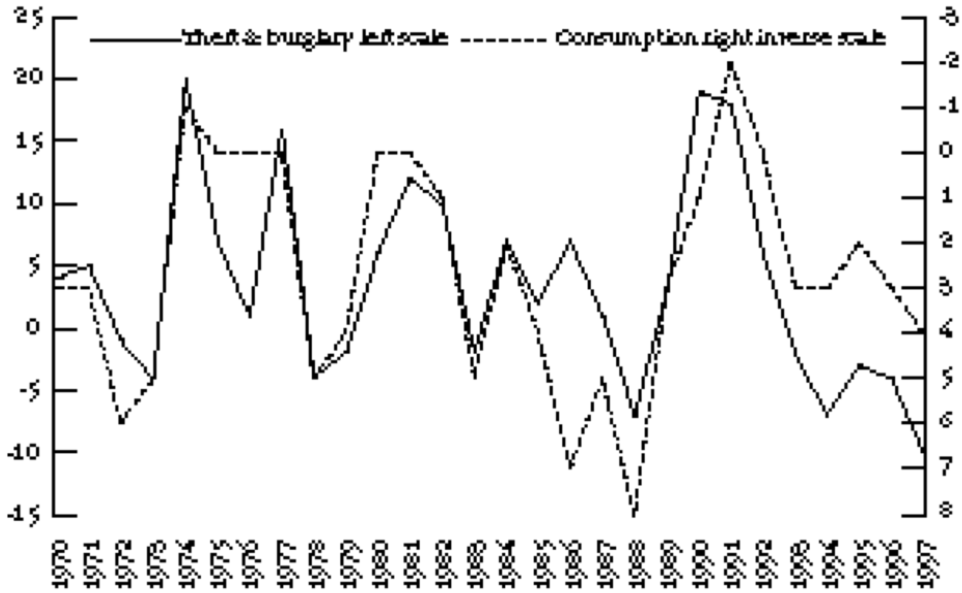
This section dwells on some theories longer than others, but this should not be taken as an indication of credibility. Again, the intention here is to promote and enhance the debate around drivers of crime. What follows is not intended to be a definitive verdict on any one theory. The longer descriptions given to some are mostly a reflection of the degree to which the authors felt that research carried out for this paper *added* something to the existing evidence. For brevity, the theories were sub-divided into six categories, though this is by no means an exhaustive list.

Economic Theories

There are essentially two theories of how economic conditions might drive crime trends and they operate in opposite directions. Under the first hypothesis, as a society gets richer crime will go up because there are more goods to steal and more people go out and socialise (and consume alcohol), which leads to more violence. Under the second hypothesis, crime goes up instead during times of economic hardship because people have less money so the motivation to steal is greater, and poverty causes antagonism between groups driving up violence.

Field (1990) studied these effects using national-level crime trends in England and Wales from 1950-1989 and concluded that for short-term trends in property crime the `motivation' effect (the second hypothesis) was more important. Field found that as personal consumption growth increased and the economy improved, property crime decreased and that this relationship, "has held throughout the twentieth-century and been particularly strong in the last twenty years" (1970-1990), see Figure 18 below.

Figure 18: Annual percentage change in theft and burglary and in consumers' expenditure



Source: Field, 1990

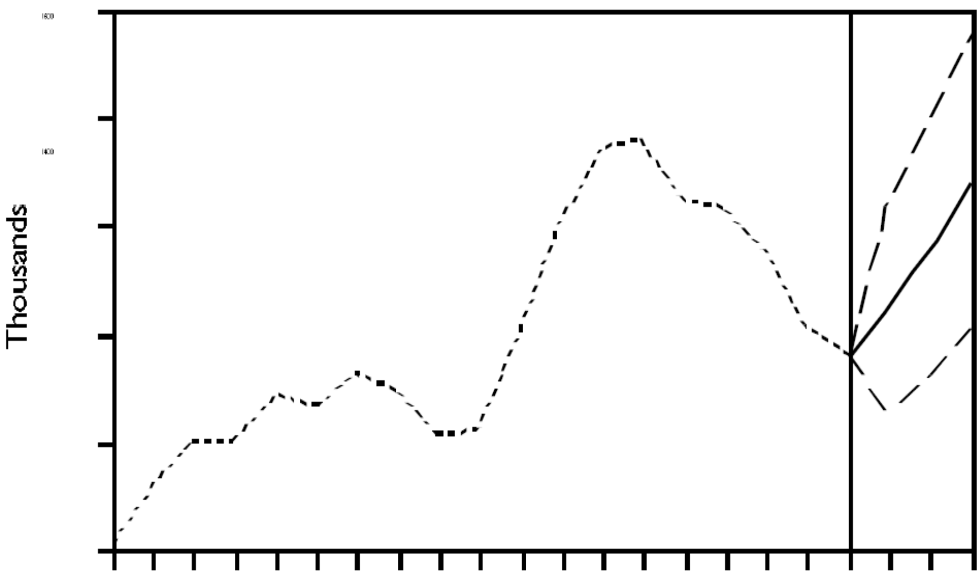
Conversely though, the data also suggested that personal crimes (i.e. violence) *increased* in line with consumption growth. This was due, according to Field, to increased affluence leading to more socialising and higher beer consumption, which was also strongly linked to violence in the findings. Field used these relationships to explain fluctuations in crime trends through the 1980s. Personal consumption growth fell during the 1980-81 recession, which provides an explanation for both the marked growth in property crime and the much more muted growth in violent crime. This situation reversed in 1987-88 when consumption grew very quickly; and this was mirrored by a slow-down in the growth in property crime and acceleration in the growth of violence.

Field's results also suggested that there was no relationship at all between unemployment and property crime once the effect of personal consumption was taken into account. He went on to explain that when unemployment is the only economic variable in an explanatory model of crime trends it is likely to register a relationship because it tends to fluctuate in line with consumption but with a lag: when personal consumption falls unemployment tends to rise shortly afterwards. This is a crucial finding for the analysis presented in this paper, which – unlike Field – uses sub-national recorded crime data. At the police force area level, consumption data is not available for that period but unemployment data is. Following Field (1990) then we might still expect to see a relationship between unemployment and theft-type crimes at the local level – as it will be picking up a more muted version of the stronger relationship with consumption.

It is important to note that all the relationships mentioned above, according to Field, only hold in the short-term. That is, they purport to explain only the fluctuations in growth rates of crime. They are not explanations for the fact that over the long-term, recorded crime of all types showed consistent growth. Field tackled long-run effects in a follow-up paper (Field, 1999), which concluded that for acquisitive crimes, the stock of crime opportunities (measured by the sum of real consumers' expenditure in each of the last four years) and the number of young males in the population were the most important factors. He found that these variables determined the `equilibrium level of crime' and that short-term effects (like changes in consumption growth) served to pull crime away from this equilibrium. This deviation from the equilibrium level would then be followed by a sharp reversion, as crime levels returned to their long-run path. Field (1999) claimed this model "appears to explain the downturn in recorded property crime in the period since 1992". However, the model also predicted "strong upward pressure on property crime" from 1998. This, as we now know, never emerged.

Many subsequent authors built on these econometric models, but most ultimately suffered from the same issue. Most models, because they were based on data showing growth in recorded crime for forty years, predicted that the mid-1990s downturn was simply a `correction' caused by the incredibly fast crime growth of the early 1990s and that crime would soon inevitably resume its long-term upward trend. Below, for example, is a prediction of burglary levels from Dhiri *et al*, 2000. Their model suggested burglary would return to almost peak levels in the three years from 1998 to 2001, see Figure 19. Instead, recorded burglary actually fell a further 20% during that time.

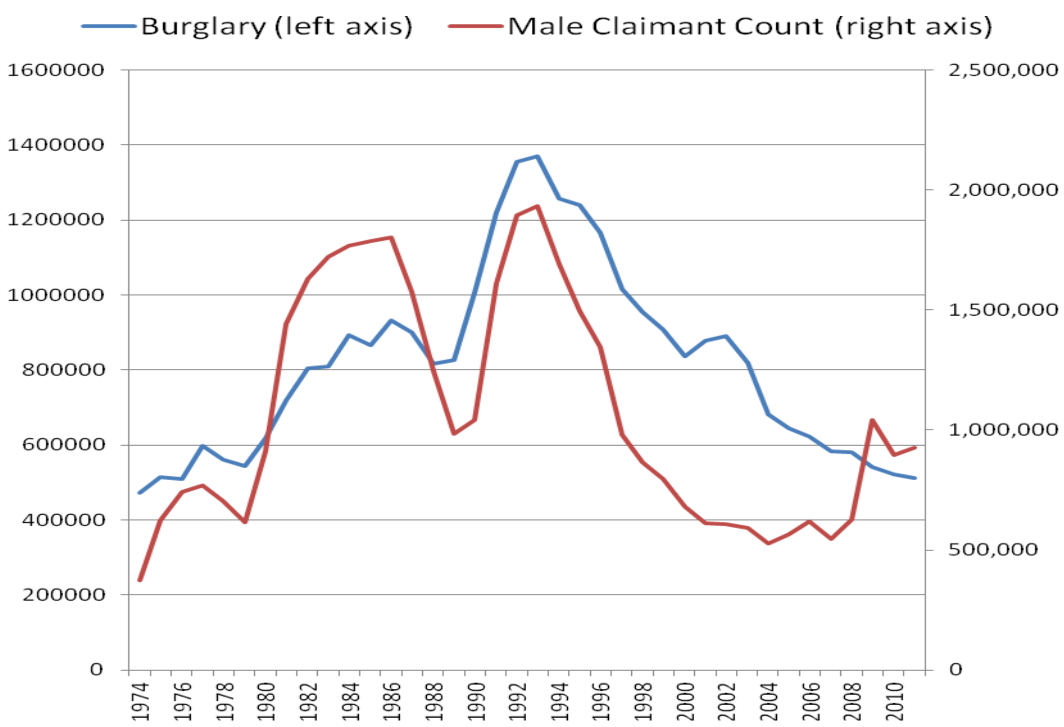
Figure 19: Burglary trend with modelled predictions



Source: Dhiri *et al*, 2000.

However, faith in the link between the economy and crime persisted into the 2000s in part because, despite the prediction failure of the models, the downward trend in crime was matched by the long period of benign economic conditions. Unemployment was still seen by many as an important variable and this was helped by the fact that it also spiked in line with crime in 1993, as shown in Figure 20 below.

Figure 20: Comparison between trends in burglary and unemployment, proxied by male claimant count



Source: ONS, Police Recorded crime; NOMIS.

At the same time, other authors suggested that variables other than consumption, GDP or unemployment might best describe the link between the economy and crime. For example, Machin & Meghir (2004) found a relationship between crime and changes in low-level wages, while Rosenfeld *et al* (2007) suggested that *perceptions* of economic conditions had the strongest relationship with crime.

Ultimately though, all theories linking the economy to crime have looked less secure in the years since the financial crisis of 2008 when (virtually) all economic indicators took a turn for the worse, yet crime in England and Wales continued its gradual decline, seemingly without a blip of any kind, as Figure 20 above shows.

There are at least three potential explanations for the fact that economic trends seemed to correlate with crime in the past, but not now, which are not mutually exclusive.

The first is the most obvious – that correlation does not prove causation and hence that the previous relationships between crime and the economy were in fact largely spurious. This argument rests largely on the possibility – which seems to fit current data - that while economic variables remain good predictors of crime levels cross-sectionally (the CSEW consistently finds that crime is highest in the most deprived areas), *changes* in deprivation or economic conditions at the individual, family or neighbourhood level do not seem to drive *changes* in crime. This would be the classic sign that deprivation is a correlate rather than a cause of crime. But in fact, the evidence suggests a more complicated relationship. For example, Farrington (2007) finds that socio-economics does predict future offending at the individual level, independent of other variables. And Weatherburn and Lind (2006) also find a relationship at the neighbourhood level with complicated generational interactions. They find that the level of deprivation exerts a small effect on offending directly but a larger effect indirectly (and inter-generationally) by disrupting the parenting process (ibid.). If this is the main path by which economic factors drive crime, it might help to explain why areas high in deprivation tend to have higher crime but why there has been no immediate temporal link between changes in deprivation and crime in the recent downturn, as any such link would take a generation to play out.

The second possibility is that this recession was different from previous ones in some important way for crime. There is some evidence for this. Though unemployment rose in 2008, the rise was not as dramatic as in earlier recessions; and though cuts to household consumption were actually worse than in previous recessions, the type of reductions were different, with a greater reliance on cutting back on nondurable expenditure and less of an effect on durable items (Crossley *et al*, 2013). This could suggest that people were not finding it as hard to purchase essential items like food. Also, as US criminologist Richard Rosenfeld has argued, the economy entered the 2008 recession with historically low levels of inflation. This was the opposite of earlier downturns, which had shown strong links with crime. Perhaps even more importantly though, as the Institute of Fiscal Studies has shown, income inequality actually decreased from 2008 to 2012 (in sharp contrast to earlier recessions) as real earnings for those in work fell, while benefits and tax credit incomes remained robust (Cribb *et al*, 2013). So if income inequality or bottom-decile incomes are the most important factors, which is in line with the Machin/Meghir hypothesis above, then it is not surprising that there has been no crime rise in the recent downturn.

The third possible reason is the most complicated. It is possible that economic factors interact with another factor (or factors) that was present in the recessions of the early 1980s and early 1990s but was not present in the recent downturn. This is explored further in Chapter 5 which contains some tentative evidence that the high levels of unemployment had an effect on crime by exacerbating the spread of the heroin epidemic.

Overall then, whilst the credence of economic theories of crime are probably currently at an all-time low,[21] this may be an over-reaction to the failure of the predictive models in the recent economic downturn. Given the evidence above, it seems likely that economic factors do have some effect on offending though this may vary over time (and hence be small currently), and may even operate mostly with a generational lag. Thus, while larger future effects cannot be ruled out, the evidence does not seem to suggest that economics, on its own, was the main driver of the recent crime decline.

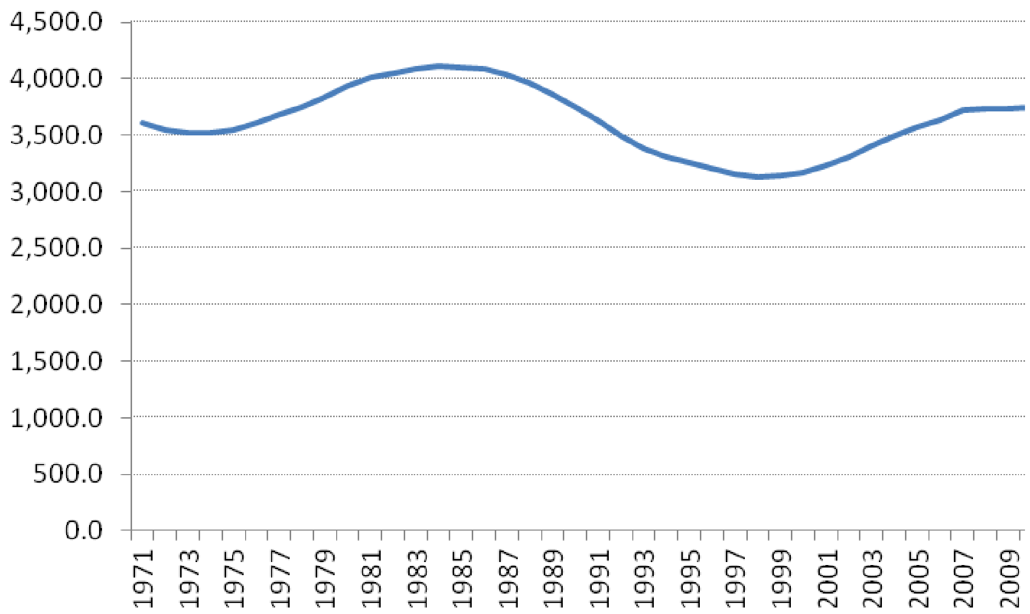
[21] University of Cincinnati professor, John Eck, who teaches criminal justice research methods and his written widely on crime and policing, was recently quoted in the Daily Mail as saying that: "The connection between crime and the economy is an illusion." See: http://www.dailymail.co.uk/news/article-2039269/Violent-crime-falls-U-S-ageing-population-tough-jail-terms.html

Offender-Based Theories (demographics, lead, civilising process and abortion)

Another set of theories argue that changes in the level of crime have been caused by changes in either the stock of potential offenders or in their propensity to commit crime.

The most straight-forward of these relates to demographics. If the number of people in society rises then we should expect more offenders and hence more crime, all else equal. This can be refined by looking at volume changes in the segment of the population particularly prone to crime, which according to the vast majority of the research evidence, is young males, see Figure 21.

Figure 21: Estimated trend in resident population males aged 15-24 in England & Wales (000s), 1971-2010



Source: ONS

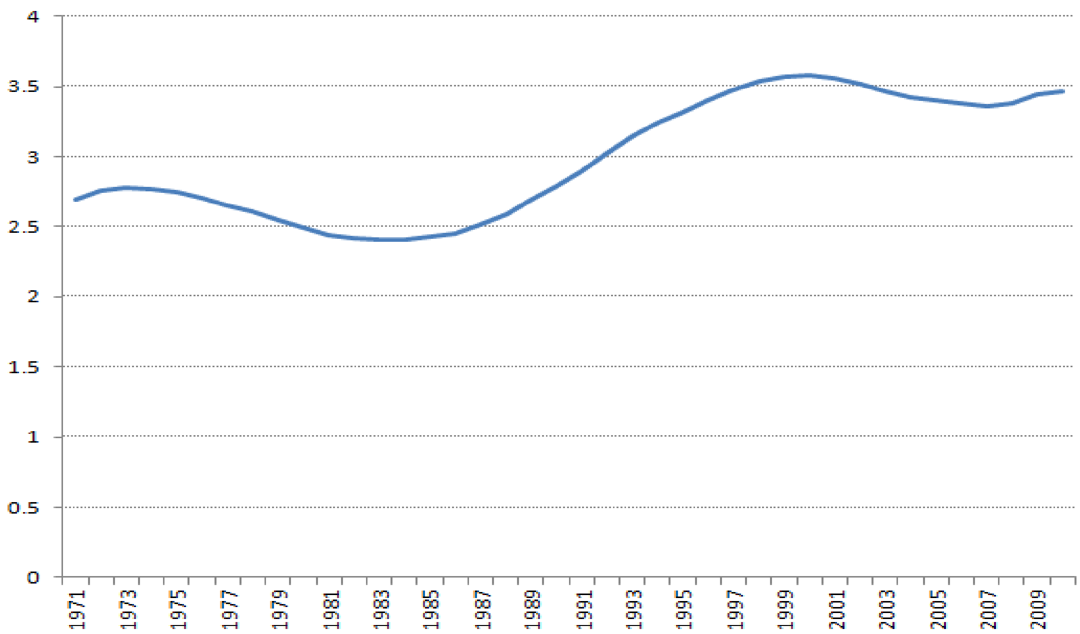
It is clear that following this theory stringently we would expect crime to have risen in the late 1970s and early 1980s, as it did, but would also have expected the turning point to have occurred earlier and for the crime decline to have ended around 1999. As the chart shows, the sheer number of young males is higher now than it was in 1995, yet CSEW crime has more than halved since then.

There is a variant on the pure demographics approach which purports to explain this discrepancy. It is often referred to as the `ageing society' argument. Whilst the *number* of young males has increased slightly, the number of older males has increased more. This means that the *ratio* of old to young has also risen, due to increased longevity and declining fertility rates.[22]

[22] Since 2001, net inward migration has also played an important role.

Some argue that the fall in crime may be associated with this ratio. Older people have low rates of criminality and tend to score higher on measures of community engagement, and hence may act as pro-social role models for the younger generation (Healy, 2004). This last part is crucial. Numbers of young males have risen since 1995, so just because there are also greater numbers of older people committing very little crime cannot have caused the crime drop on its own. An ageing society can only help to explain the crime fall if the ratio of young to old actually *changes* the behaviour of the young. The change in the ratio through the crime turning point is shown in Figure 22 below.[23]

Figure 22: Ratio of males aged 40+ to males aged 15-24 in the population of England and Wales, 1970-2010



Source: ONS

The chart shows that from 1971 to about 1987 there were around two-and-a-half males aged 40+ for every male aged 15-24, but through the period from 1987 to 1999 this increased to around 3.5, where it has more or less stayed since. Hence, on average, a young person in 2012 would be more likely to have contact with older, non-offending individuals than a young person in 1986. This in turn could have influenced behaviour either through a normalising effect – the number of non-offenders increases therefore it is more normal *not* to offend – or more directly through a role-model effect.

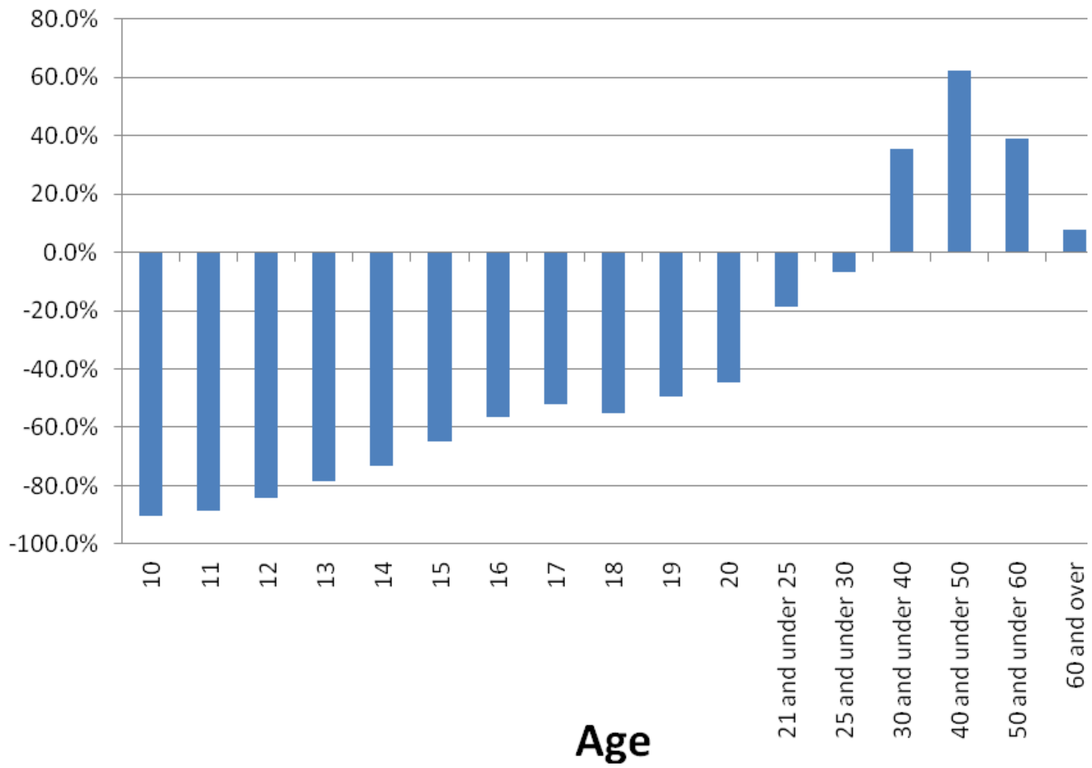
But the timings are not perfect. Certainly the ratio of old-to-young did shift and the biggest shift occurred (loosely) around the period of the crime turning point. But the ratio was also increasing markedly during the early 1990s when

[23] To look at the ratio of young-to-old, the category 40+ was selected not because of any judgement that people over 40 should be considered `old' in a wider sense. It was selected because most evidence suggests that average crime rates are very low by the time individuals reach that age. (Farrington, 1986)

crime was rising fastest and there is nothing in Figure 22 to suggest why crime has continued to fall from 1999 through to today (2013).

Furthermore, one other fact, while not disproving the ageing society hypothesis, perhaps provides further reason for doubt. The rate of crime amongst old people actually *increased* through the crime decline, which somewhat undermines the likelihood of a significant role model effect. That the *volume* of crime amongst old people will have increased should not be surprising. Crime volumes would be likely to rise amongst older people simply because there were more of them. But, as Figure 23 below shows, even the *rate* of proven offending amongst older groups increased between 1995 and 2012. Taken together, these facts tend to suggest that the drop in crime in England and Wales has been driven by the younger generations, and that the drop has come in spite of the behaviour of the older generations, not because of it.[24]

Figure 23: Percentage change from 1995 to 2012 in rate per 100,000 population found guilty or cautioned for indictable offences, by age



[24] One possible counter-argument is that Figure 23 reflects the changing nature of crime rather than a slight shift in offending from young to old. If, as some argue, there has been a shift in acquisitive offending from burglary and vehicle crime to cyber crime and fraud, both amongst offenders and in terms of the attentions of the police, perhaps this is the reason behind the figures? This explanation does not stand up to close scrutiny however. Breaking the proven offenders' statistics down into offence types shows that the number of proven offenders, aged over-21, who were convicted of fraud actually fell by 4% between 2000 and 2012. Whereas the numbers committing burglary, robbery and drug offences rose by 10%, 34% and 36% respectively.

Another offender-based theory was put forward by Donuhue & Levitt (2001). They suggested that a major reason for the crime decline in the US was the legalisation of abortion a generation before. They argued that this would have reduced the stock of potential offenders in the 1990s both directly by reducing the number of people born and indirectly due to the fact that cohorts of people born post abortion-legislation might have lower offending propensities. This would be the case, according to the authors, if "women who have abortions are those most at risk to give birth to children who would engage in criminal activity" (Donohue & Levitt, 2001).

Likewise, the so-called `lead hypothesis' comes to an identical conclusion through an entirely different mechanism. It posits that the propensity of offending would have risen and fallen with the level of lead in the atmosphere (which peaked in most nations in the 1970/80s) because lead levels have been shown to increase aggression and lower educational attainment (Needleman *et al*, 2002; Wright *et al*, 2009 and Chen *et al*, 2007). Like the abortion hypothesis, the `lead effect' on crime would occur with a generational lag. That is, the declines in crime would only be expected to occur once the children experiencing lower lead levels reach the age at which they might otherwise have commenced a life of crime.

Various studies have tested these theories, some supporting and some refuting the original claims, and it is beyond the scope of this paper to add anything much to these debates.[25] There is, however, one important point to be made about these theories and their relationship to the trends in the previous section. Because they work on a generational basis, any rise or fall in crime predicted is likely to be *gradual.*[26] Changes that affect crime propensity a generation earlier are likely to feed through to current trends slowly, as successive cohorts of offenders become more or less crime prone and previous cohorts gradually age in or out of offending. There are certainly hints of this kind of process underlying many of the trends studied (particularly the more gradual falls in non-acquisitive crime like vandalism and the gradual ageing of offenders). But, it seems unlikely that these can be the main drivers of the acquisitive crime `spikes' visible in many areas of the UK in the 1990s.

This is even more obviously true of the final offender-based theory in this section: the civilising process. Stephen Pinker (2008), following Norbert Elias (1969; 1982; 2000) suggests that over the long-term, the decline in crime has

[25] For supporters of the lead hypothesis see Nevin, 2007 (http://mpra.ub.uni-muenchen.de/35338/1/MPRA_paper_35338.pdf) and Reyes, 2007, (http://www3.amherst.edu/~jwreyes/papers/LeadCrime.pdf for detractors, see Moffitt, 1996 (http://jama.jamanetwork.com/article.aspx?articleid=395806) and Kaufman, 2001 (http://courses.washington.edu/bethics/Lead/Kaufman2001reply.pdf). For further supporters of the abortion hypothesis see Charles and Stephens, 2006 (http://www-personal.umich.edu/~mstep/abortion_final.pdf) and Sen, 2007, (http://www.degruyter.com/view/j/bejeap.2007.7.1/bejeap.2007.7.1.1537/bejeap.2007.7.1.1537.xml) , for detractors see Kahane, 2005 (http://eprints.lancs.ac.uk/48810/1/Document.pdf) and Joyce, 2004 and 2009 (http://piketty.pse.ens.fr/files/Joyce2001.pdf).

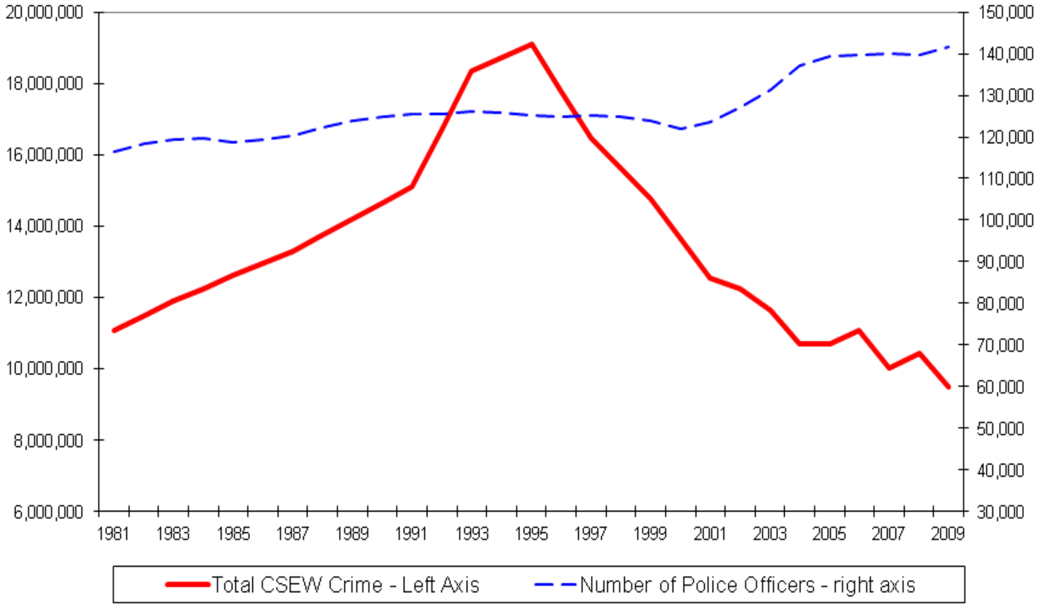
[26] Indeed, preliminary modelling suggests that it is questionable to test for straight correlation between trends in lead and trends in crime a generation later (using a fixed lag) because this does not take into account the age-crime curve. Our modelling suggests that even if a sharp drop in lead levels did cause change in crime propensity a generation later, this would manifest itself in crime trends with a much more gradual downward trajectory than the downward trajectory in lead.

been at least partly brought about through a gradual civilising of the population. Pinker's analysis is focused primarily on violence, but it seems plausible that increased civility might have an impact on theft too. Again though, this hypothesis is not tested here. Instead, it is simply noted that whilst this could have an important effect on the long-term path of crime, it is unlikely to have been a factor in causing the dramatic rise and then fall in property crime in England and Wales during the mid-1990s.

Criminal Justice System Theories

Some commentators have sought to link changes in crime levels to changes in policing or to levels of incarceration. Policing theories can be divided into two: those that focus on police resources and those that focus on police tactics and techniques. The former is a fairly obvious formulation: if police resources increase, crime might be expected to fall and if resources decrease they might be expected to rise. Many studies have attempted to test this hypothesis with mixed results.[27] But whatever the specific relationship between crime and police resources during this period, it seems unlikely that it played an important part in the crime turning point in England and Wales, for the simple reason that there was no marked change in police officer numbers at this point, see Figure 24 below:

Figure 24: Crime and police officer numbers in England & Wales



Sources: CSEW, Home Office Police Statistics

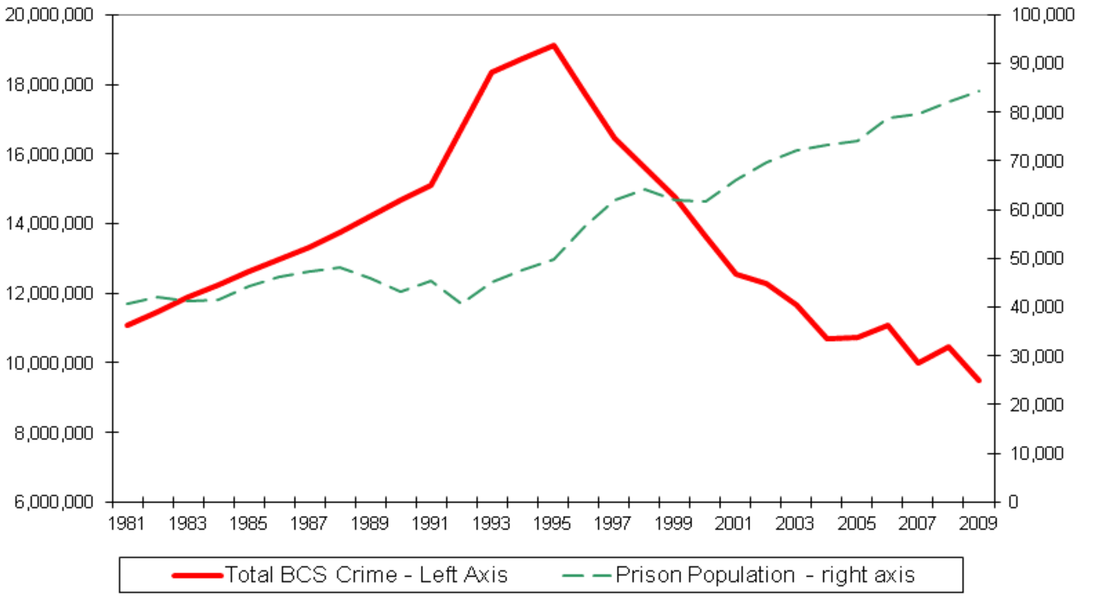
The other way in which policing might affect crime levels is through improved tactics and techniques. Even if police resources stayed much the same, if police tactics improved significantly then crime might fall as a result. This has been cited as a major reason for the crime decline in the US, particularly in New York City (Zimring, 2007; 2011). In England and Wales too, some have linked the falling crime trend to improvements in policing, either in detection

[27] See for example: Klick & Tabarrok, 2005; Evans & Owens, 2007; Hamed & Vollaard, 2012.

rates (Bandyopadhyay *et al*, 2012), the move to neighbourhood policing (Quinton *et al*, 2008) or more targeted policing (*The Economist*, 2013). Again, it is beyond the scope of this paper to test these claims, but it seems unlikely that the sharp spikes in crime visible in the local-level trends in the mid 1990s can have been due to sharply worsening and then improving police tactics.

For the most part, studies that have looked at the relationship between incarceration and crime levels have yielded significant but small effects.[28] Overall, they suggest that increases in the prison population have probably played some role in the crime decline but that they are unlikely to be the main driver of trends. The mid 1990s turn-around in crime in England and Wales did coincide with an increase in the prison population, see Figure 25 below.[29] This is explored further in Chapter 3.

Figure 25: Crime and the prison population in England & Wales



Sources: CSEW, MOJ Prison Population Statistics

<u>Opportunity & Security Theories</u>

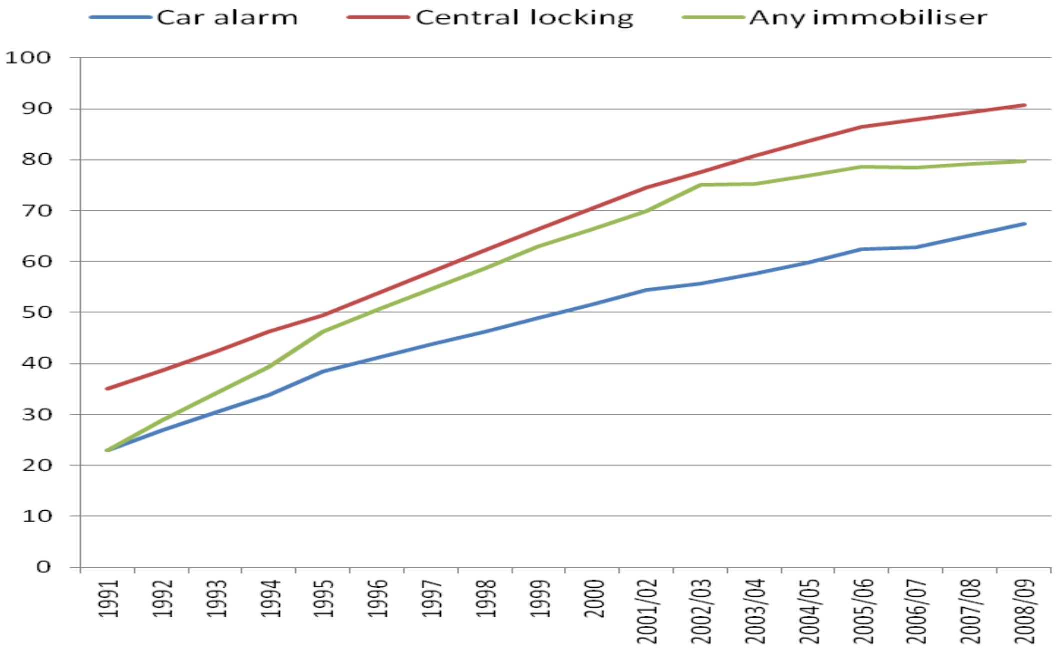
These theories suggest that crime's rise and fall can be explained not by changes in the offending propensity of individuals but by changes to the crime environment. Put simply, these theories suggest that crime will flourish in conditions when it is easy to commit, and diminish when this ease is removed. Proponents of this theory explain the long-term, pre-1995, rise in burglary by citing factors like the expansion in female employment, which left more houses empty during the day. In a similar vein, the rise in shoplifting is explained by the shift of items to the shop floor where they are far more

[28] For a review see Durlauf and Nagin, 2011: http://www.public.asu.edu/~gasweete/crj524/readings/04-12%202011-Durlauf-Nagin%20(imprisonment%20and%20crime%20-%20can%20both%20be%20reduced).pdf
[29] The relationship appears stronger if we take into account the likely lag on the CSEW – see footnote 6 above. However, there are too few data points over this period to draw firm conclusions.

accessible to thieves; the rise in vehicle theft is linked to the number of cars on the road, and so on (Ross, 2013).

Under this hypothesis, the fall in crime can be explained by security improvements that made these offences harder to commit. Immobilizers in cars are the most studied example, though high-quality locks on houses and burglary-proof windows and doors have also been cited.[30] As Figure 26 below shows, the proportion of cars with immobilizers, and other security features, increased markedly through the 1990s and 2000s.

Figure 26: Percentage of CSEW respondents with security devices installed on their main vehicle, 1991 to 2008/09



Source: CSEW.

Furthermore, studies have shown beyond doubt that fitting an immobilizer to a car makes it less likely to be stolen - around 80% less likely, according to Ours and Vollaard, 2013. It is important to note that this in itself does not prove a causal link between immobilizers and declining vehicle thefts. If there are still enough (older) cars on the road which do not have immobilizers, and thieves switch to these, then it is possible that just as many cars might have been stolen as before. There is strong evidence that thieves *did* adjust in this way (Brown and Thomas, Ours and Vollaard, 2013). But logic dictates that once the pool of cars with immobilizers grew to a certain level, overall thefts would likely decline as thieves found themselves deterred more often. One sign that this occurred in the mid 1990s, as the number of cars with

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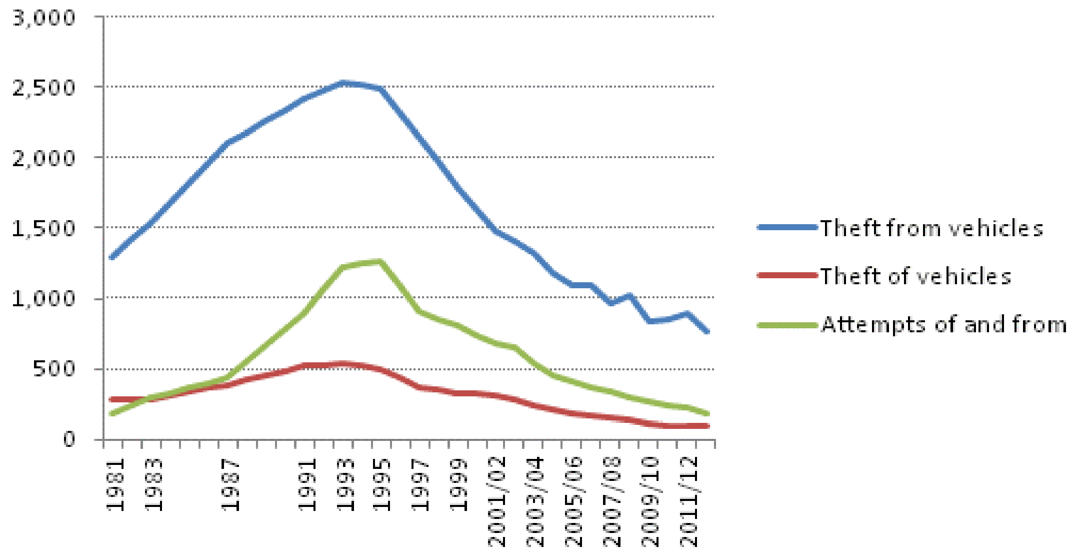
[30] See Farrell et al, 2011 (http://www.sfu.ca/content/dam/sfu/icurs/Publications/2011/Farrell,%20Tseloni,%20Tilley.pdf) on immobilizers and Vollard & van Ours, 2010 (http://ist-socrates.berkeley.edu/~raphael/IGERT/Workshop/Crime-March2010.pdf)

immobilizers grew, was that attempted (but ultimately failed) vehicle thefts increased sharply:

Figure 27: Vehicle theft and attempted vehicle theft, 1981 to 2012/13



Source: CSEW

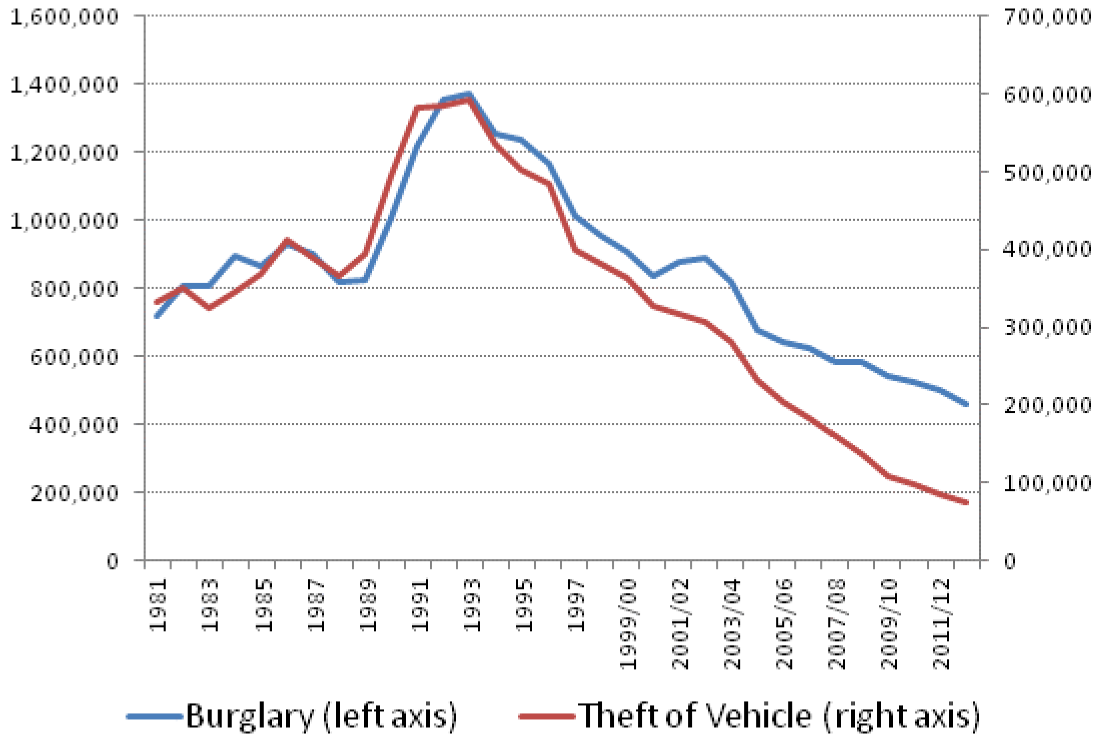
Some international evidence also supports an “immobilizer effect”. Australia and Canada had sharp falls in vehicle theft exactly in line with legislation to make immobilizers mandatory on all new cars. MM Starrs Pty Ltd (2002) evaluated the immobilizer law in Western Australia and found that it had quite a large effect: a 19% reduction in opportunistic, joy-riding thefts, in which the vehicle is ultimately recovered. However, the study found that the law caused only a 2% fall in professional thefts, in which the car was not recovered but was (in all likelihood) shipped abroad or broken down for parts. The latter class of theft is probably undertaken by more accomplished thieves, who may be less deterred by immobilizers.

No study (that could be located) has attempted to quantify the immobilizer effect in England and Wales, but as in Australia there has certainly been a greater reduction in opportunistic thefts, in which the vehicle is recovered, compared to “professional” thefts, in which it is not. The latter now make up more than 60% of all vehicle thefts, up from less than 40% in 1995.

But the evidence in other nations is less conclusive. Vehicle theft in the US, for example, fell at a similar rate to that in England and Wales from 1991, well before immobilizers had reached the degree of penetration that would be likely to have caused such an effect. It is possible that other security devices – notably Lo-Jack - may have caused the decline instead (see for example Ayres and Levitt, 1998), but it is also possible that other factors were involved.

On balance, the evidence that the increasing trend in car security would have driven down thefts of vehicles is fairly strong. Some questions remain, however. Firstly, if opportunity and security were the only factors of importance, why would vehicle crime have *increased* so dramatically in the early 1990s when (as Figure 26 shows) security levels were rising at this time – albeit from a low level? Secondly, for immobilizers to be the most important factor in the 1993 crime turning point for theft of vehicles in England and Wales, it would be necessary to believe that a dramatic `tipping point' occurred when penetration of immobilizers was around 35%. It is not immediately clear why this might be the case. Thirdly, the logic of the immobilizer argument suggests that change would be gradual at first – as the pool of cars with immobilizers grows and then faster as it approaches critical mass, but the trend in vehicle theft does the opposite: the decrease is most pronounced immediately after the peak. Finally – and most importantly – we have seen that many types of acquisitive crime peaked and fell *at the same time* in the mid 1990s. Figure 28, below, shows this even more clearly. Is it possible that security levels relating to both burglary and theft of vehicle rose and fell together to such an extent as to create an almost identical trend through the crime turning point? Or was some other mechanism driving both trends until around 2000? (At which point the vast majority of cars had immobilizers and theft of vehicle began to fall faster.)

Figure 28: Police recorded burglary and theft of vehicle trends, 1981 to 2012/13

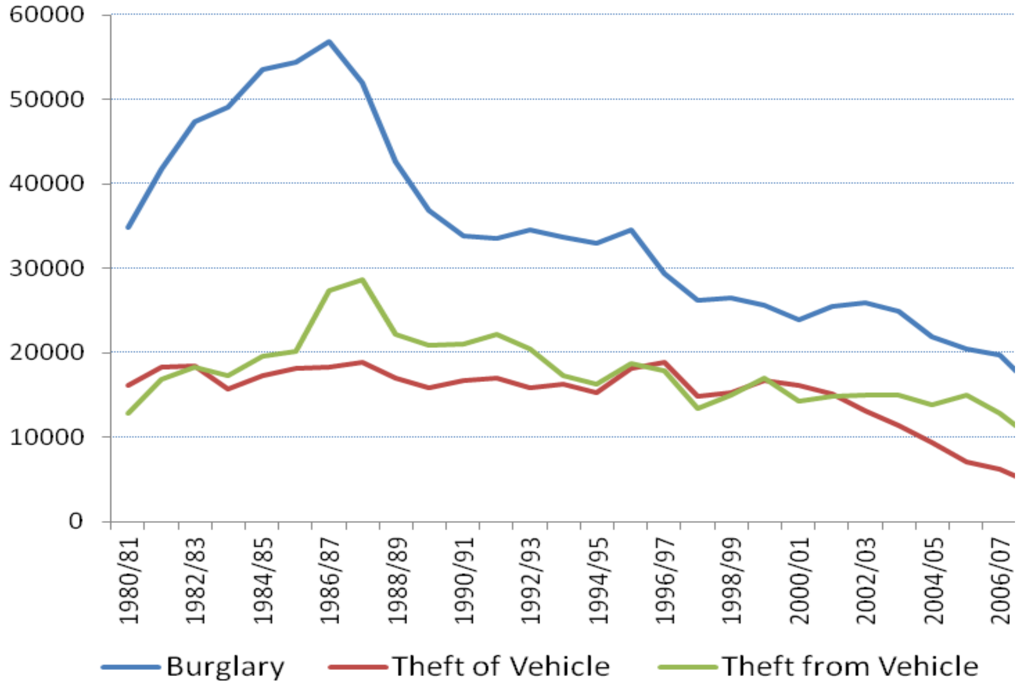


Finally, how do over-arching changes in opportunity and security fit with the evidence that different parts of England and Wales had sharp `spikes' in acquisitive crime at different times?

Merseyside again provides an illuminating example in this context. Unlike nationally (and in most other police force areas – see Appendix 2), trends in the three most reliably recorded types of theft do not rise and fall together in

Merseyside. Burglary and theft *from* vehicle show a clear mid-1980s peak, but theft *of* vehicles remains pretty flat until around 2000 when it starts to fall markedly. This may imply that if immobilizers drove down vehicle theft, they did so once penetration had reached a high level, which was well after the crime turning point in most areas.

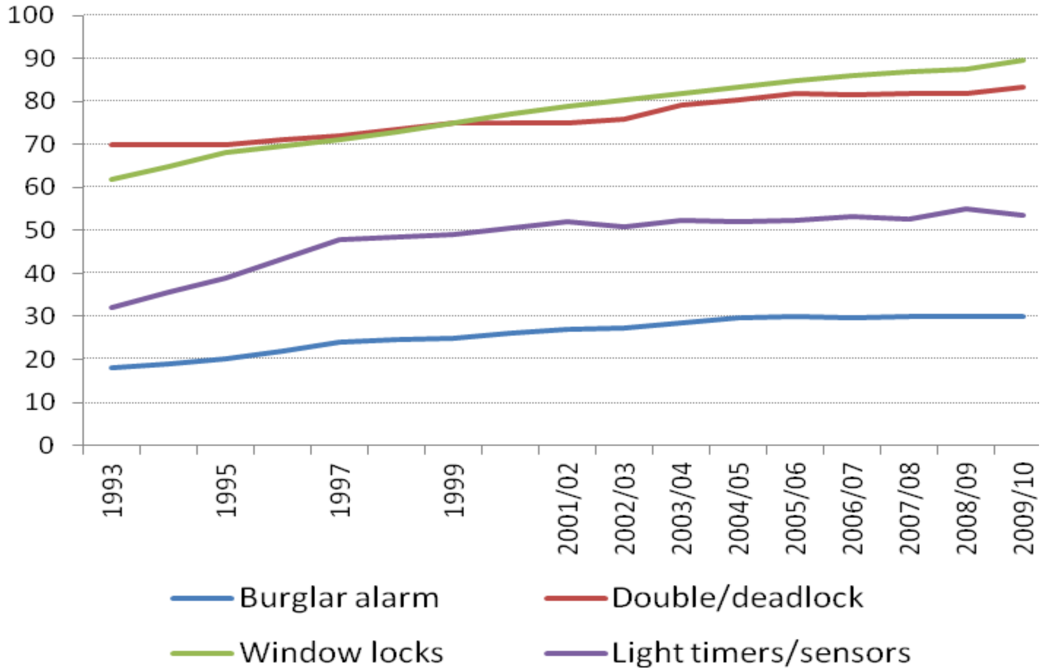
Figure 29: Volumes of recorded offences in Merseyside



Source: ONS, police recorded crime.

Broadly speaking, proponents of the security hypothesis have produced three different sets of evidence to answer these questions. Firstly, supporters point to similar increases in house security to explain the concurrent decline in burglary – see Figure 30 below:

Figure 30: Percentage of households in England and Wales with different security devices, 1993 to 2009/10

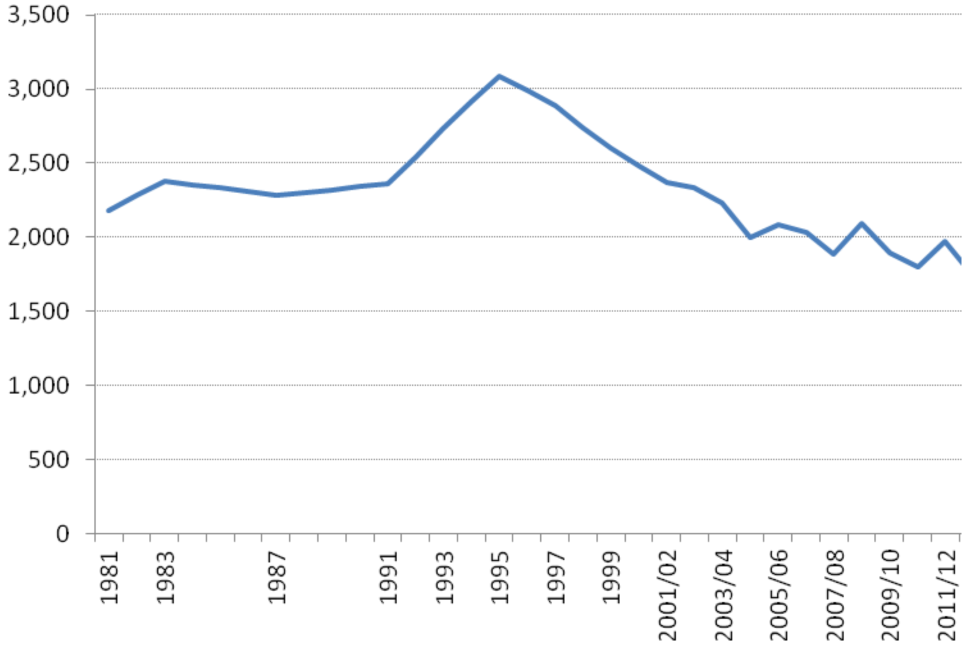


Source: CSEW

As with cars, there is also good evidence that households with better security suffer lower rates of burglary victimisation (Vollaard and van Ours, 2011). So it does seem likely that the increasing use of these security devices has helped to bring down burglary. A paper by Vollaard and van Ours (2011) find that regulation requiring that all new-built homes in the Netherlands had to have burglary-proof windows and doors reduced burglary rates by 26%, with no displacement to other crimes. But it is more questionable to cite this evidence in relation to crime's turning point. Generally, these security measures had reached higher levels of penetration than immobilizers by the mid-1990s meaning that their `tipping point' would have to be different. And this also implies that security levels were increasing during the early 1990s, when burglary was rising at its fastest rate.

Furthermore, personal theft, which is unaffected by these security improvements in a direct sense, also shows a clear mid-90s peak, according to the CSEW – see Figure 31 below.

Figure 31: Total incidents of personal theft (000s), CSEW



Source: CSEW

These similarities in trends, despite differing levels of security, bring us to the second set of evidence offered by proponents of the security hypothesis. They argue that security improvements in vehicles simultaneously prevented other offences, either because stolen vehicles are used to commit other crimes like burglary, or because vehicle theft is often a debut crime and so preventing it might prevent progression to other offences (Farrell *et al*, 2011). This again, is certainly possible, but strong evidence of these cross-crime effects is lacking, to our knowledge, and some previous break-through improvements in car security have apparently caused the opposite effect. That is, as cars became harder to steal, thieves switched to other types of acquisitive crime. This seems to be what happened when the government of East Germany legislated that all cars (not just new ones) had to be fitted with steering locks from 1961. The effect on vehicle theft was immediate: it fell by around 15% in a year (Webb, 1997). But there was also evidence of displacement, as motorcycle thefts increased markedly from the date of the new legislation; and there was no obvious effect at all on the trend in theft *from* vehicles, which continued to rise (ibid.)

The situation in the mid 1990s was quite different. There is no real sign of substitution into other crimes. All the crime types seem to rise and fall together. Farrell (2011a) notes that one exception to this was mobile phone theft, which isn't itself a category on either recorded crime or the crime survey, but has been measured via questions relating to items stolen. It did increase through the late 1990s and early 2000s, just as other acquisitive crime types declined and opportunity seems the most obvious reason: just as cars and houses became harder to break into, people started carrying a valuable item around on their person or in handbags.[31] So it makes sense that there would be a switch in offending patterns. But, as Figure 7 showed, in terms of the overall trend in acquisitive crime, this substitution effect plays only a minor role. Overall the *propensity* for acquisitive crime seems to have declined hugely from the mid 1990s.

This leads to another branch of the opportunity/security hypothesis, which initially seems to offer a potential explanation both for the similarity in acquisitive crime trends *and* the sharp rise that preceded the crime decline. It is outlined in a paper by Marcelo Aebi (2004), who suggested that the sudden shift upwards and downwards in acquisitive crimes in the early 1990s was due to equally radical changes to the stolen goods market. He writes:

"*The fall of the Berlin wall in 1989 produced a substantial modification of crime opportunities by putting in contact two parts of the continent (of Europe) that differed dramatically in wealth; thus, within a few months, a substantial market for stolen products, including stolen cars, jewellery, electronic devices and even clothes emerged in Central and Eastern Europe... In that context, the increase in all kinds of property offences registered on the wealthy side of Europe at the beginning of the 1990s seems quite logical...The decrease that followed could be explained by the combination of at least three factors. Firstly, a saturation of the Eastern market; secondly, a reinforcement of police measures against trans-border crime, especially in countries seeking to become members of the European Union; and, thirdly, an improvement in security measures in Western European households*".

At a pan-European level, this explanation seems plausible, though there is little direct evidence relating specifically to England and Wales. In fact, others have argued that England and Wales would be less affected by these macro-European changes than other parts of Europe due to its lack of land borders, which made transportation of stolen goods to Eastern Europe more difficult and expensive (Brown & Clarke, 2004). Also, the reasons Aebi gives for the fall in crime perhaps suggest a more gradual decline as Eastern markets slowly became saturated and security gradually improved. Furthermore, it is not clear why this explanation would fit with the *local* variation in crime peaks that we saw in the previous section.

On balance, research seems to suggest that while opportunity and security levels have certainly driven trends in thefts of *individual* items, evidence is less clear that they have been responsible for the *aggregate* rise and fall in crime. Data repeatedly show that as successive product innovations come to market – from car stereos in the 1980s to smartphones recently – thefts are likely to rise with ownership, as the opportunity (number of potential victims) increases. Data also show that many security devices have been successful in helping to reverse these trends, with car immobilizers being the most prominent example. But the `immobilizer effect' seems to have been strongest

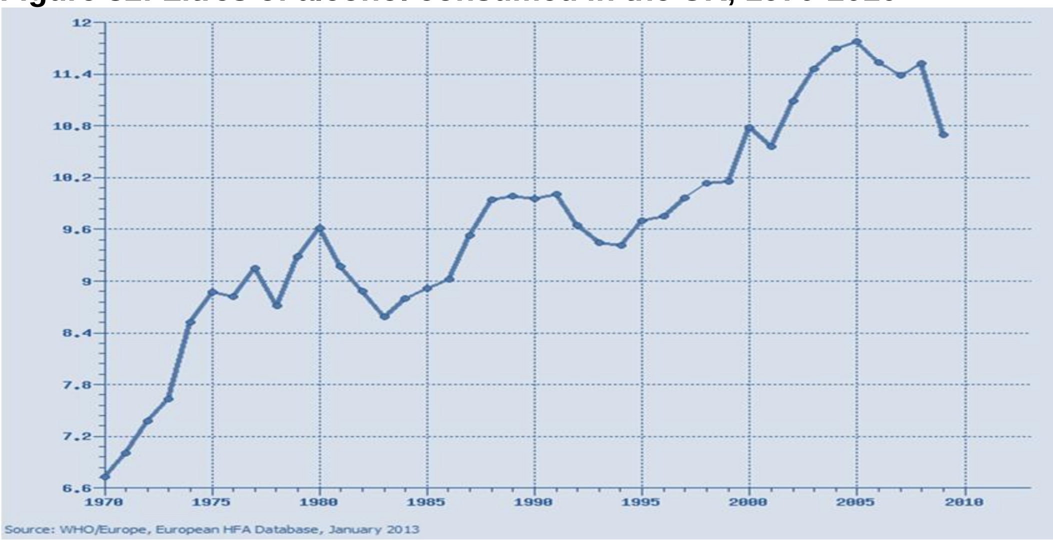
[31] Another example is credit card fraud, which surged in the 1990s in line with growth in the use of credit and debit cards to pay for everyday items. Whether this represented a real rise in overall fraud or simply a switching of fraud types is unclear (cheque fraud almost certainly declined simultaneously for similar reasons, usage fell as credit and debit cards were used instead).

from around 2000 rather than in 1993-95 when crime peaked. And research is not conclusive that effective security in one type of crime deters offenders from committing other types. At times the opposite has occurred. The fall of the Berlin Wall and the resulting explosion in the size of the stolen goods market is certainly worthy of further investigation, but like the other explanations offered by proponents of the opportunity/security hypothesis it does not seem to offer a reason for local variations, like Merseyside. In short, the opportunity/security hypothesis has probably played a role in the crime drop, but without something to explain the large and general reduction in offender propensity for crime, it probably remains only a part of the complete story.

Substance Abuse Theories (drugs and alcohol)

The final set of theories discussed here links changes in crime levels to changes in the consumption of drugs and/or alcohol. Generally speaking, the evidence on alcohol suggests that it should be considered a potential driver of violence rather than of the acquisitive crime types that have dominated overall trends (see for example Bushman & Cooper, 1990). However, it is worth noting that alcohol use in England and Wales certainly grew in line with crime, but peaked later, in 2005 (see chart below):

Figure 32: Litres of alcohol consumed in the UK, 1970-2010



Source: WHO/Europe, European HFA Database, Jan 2013.

The remainder of this paper concentrates on the other substance abuse hypothesis: that changes in drug consumption have caused changes in crime. Though some authors have linked crime to other drugs (see for example Pedersen *et al*, 2009 and Braakman & Jones, 2013), in general it is opiates and crack-cocaine that have produced the strongest quantitative links to (acquisitive) offending at the individual and cohort level in England and Wales. Evidence is so far lacking on the effect at a national level. To explore this, the next section looks at how the number of users of these drugs changed over the last 40 years.

Chapter 3: A historical overview of the spread of heroin in England and Wales

Introduction

This chapter contains a descriptive account of the heroin epidemic and its influence on the number of opiate/crack users (OCUs) from the late 1970s through to the present day (2013).

Though it is widely accepted that a heroin epidemic occurred in the UK in the 1980s and 1990s, a lack of data has made it difficult to chart the progress of the epidemic precisely (Yates, 2002; Parker *et al*, 1998; Strang *et al*, 1997). In this chapter therefore, three types of sources are combined to try and piece together what happened. These sources are:

- the limited national-level datasets available: addicts notified to the Home Office, drug seizures and drug deaths

- other evidence that could be located on the UK heroin epidemic: mainly ethnographic studies or other qualitative accounts, particularly the pioneering four-year study of qualitative and quantitative evidence from the Wirral area of Merseyside, by Howard Parker and colleagues.

- Finally, evidence on international heroin epidemics is incorporated, particularly the US model developed by Hunt and Chambers (1976).

The growth in heroin use

Available indicators and qualitative UK evidence agree that before the late 1970s, heroin use in the UK was a relatively small-scale phenomenon and crack use was essentially unheard of. Despite a few reports of small-scale `outbreaks' in places like Crawley (De Alarcon *et al*, 1968), heroin use through the 1960s and 1970s was confined largely to London and does not seem to have had a particularly strong link with crime (Parker *et al*, 1988). One study of 37 heroin users published in *The Lancet* in 1968, found that: "the commonest factors were a *high* social class background and failure to complete courses despite good educational opportunities." It also found that "there was *little association with crime*." (Italics added)[32]

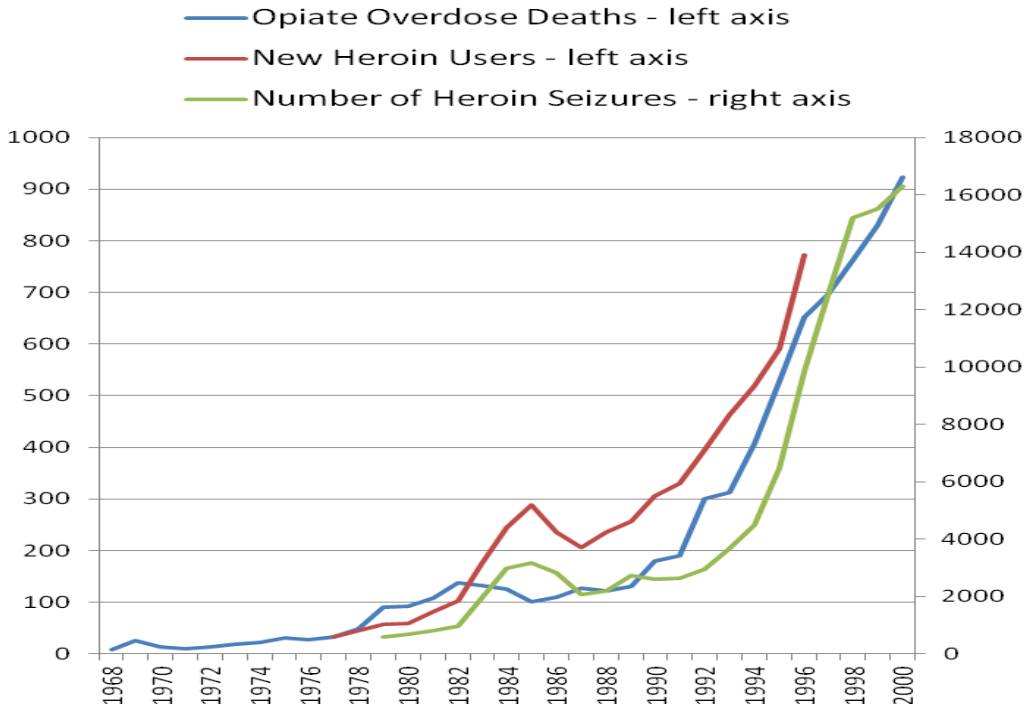
Sources also agree on the catalyst for change. Around 1977-78, a new heroin supply route opened up from Iran and Pakistan (Pearson, 1987; Yates, 2002). This made heroin more available and affordable, but equally important was that the product coming in via this new route was smoking heroin, which could not be injected without being treated with other substances, like lemon juice (Griffiths, Gossop, Strang, 1994). This had two crucial effects, both of which probably exacerbated the onset of the epidemic. Firstly, potential users put off by the thought of injection were no longer faced with that barrier, and

[32] See http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1924404/?page=1

secondly, smoking heroin came with the myth that, unlike the injection-variety, it was non-addictive (Yates, 2002). As a result, significant pockets of heroin use began to be recorded outside of London. The main indicator of heroin use at this time was the Addicts Index, a dataset of new and existing dependent drug users reported to the Home Office, largely by General Practitioners and other medical institutions.[33] In 1979, 58% of new heroin notifications to the index were from the Metropolitan Police Service area (i.e. London). By 1996, London accounted for just 18% of the total (Hickman *et al*, 2004)

Unfortunately the Addicts Index is likely both to lag and under-count the true population because evidence shows users tend not to seek medical help until several years after initiation, and some never do (Millar *et al*, 2001). However, along with other available indicators, like the number of heroin seizures and the number of opiate overdose deaths, the Addicts Index *does* give an idea of the sheer scale of the increase in heroin use that occurred:

Figure 33: Available indicators showing the magnitude of the heroin epidemic[34]



Sources: Addicts Index for new heroin users; Home Office statistics for seizures and http://aje.oxfordjournals.org/content/160/10/994.full.pdf for opiate overdose figures).

By the 1990s heroin use had increased to levels perhaps 10 or 20 times greater than during the 1970s. Using various multipliers to `correct' the Addicts Index data, it has been estimated that the total number of heroin users in England and Wales was between 10,000 and 25,000 in 1981 (Wagstaff & Maynard, 1988), but that by the mid 1980s this had increased to

[33] The Addicts Index also changed its methodology slightly in 1987, meaning that estimates for the total addicts notified are not strictly comparable before and after this point. This is why, throughout this paper, the `new heroin users' category is used where possible as this was not affected by the change.
[34] Note that the geographical coverage for opiate overdose deaths is just England, for new heroin users and seizures it is England and Wales.

60,000-80,000 (Pearson, 1987) and that by the turn of the 1990s total users were being counted in the hundreds of thousands (Sutton & Maynard, 1992). Though all estimates should be treated cautiously as they are derived by multiplying up from the imperfect Addicts Index data, it seems reasonable to use the term `epidemic' to describe the escalation in use, a label used previously by other authors (for example Parker *et al*, 1988; Ditton & Frischer, 2001).[35]

In contrast to the heroin-using population prior to the epidemic, studies found that the new users tended to be young, working class and unemployed (Pearson, 1987; Parker *et al.*, 1988).[36] For example, in a 1984/85 sample of heroin users from the Wirral area of Merseyside (one of the first areas to be affected by the epidemic according to available evidence), 87% were unemployed and the modal age was 19 (Parker *et al*., 1988). Around three-quarters were smokers of heroin; only about 25% injected at that time[37], though 72% said that they had become daily users within six months of first use (ibid.). According to the study authors, there was a, "*tragic time lag between the contagious stage during which heroin use spread and the stage when the epidemic's full impact was felt and reacted to by the community*" (Parker *et al*, 1988). Indeed, a comment by one young user appears to sum up the statistical evidence quite well:

"....*the next minute it was everywhere, like. It just sort of took Liverpool by storm*." (Jack, 22, Merseyside. From Pearson, 1987)

The way heroin use spreads

Research suggests that heroin use spreads primarily through networks of friends and relatives rather than through the marketing techniques of drug dealers. Nine out of every ten users in the Wirral said that they had first received heroin from a friend or relative, rather than from a dealer (*ibid.*). This fits the model of heroin spread developed by Hunt and Chambers (1976) using data from the UK and from the US heroin epidemic more than a decade earlier. They suggested that at the person-to-person level, heroin use spreads via *micro-diffusion.* A few 'initiators' enter a community and pass on their heroin use, through networks of friends, to susceptible individuals. These secondary users then spread heroin to their susceptible friends, and so on.

Importantly, what Hunt and Chambers (1976) found in the data was that while initiators pass on use to many people, secondary users spread heroin to a far smaller number. They produced two possible reasons for this. Firstly, an

[35] The literature on heroin use borrows much from epidemiology, and indeed the use of the word `epidemic' also derives from the evidence suggesting that the spread of heroin operated in a broadly similar fashion to the spread of a disease, see later section. The link is purely in terms of the way usage spreads rather than equating use with a disease itself.
[36] In the Wirral, during the early stages of the epidemic, Parker and Newcombe (1987) and Parker *et al*. (1988) found a male:female ratio of around 3.6:1. But there was also some suggestion that the ratio tilted slightly towards females as the epidemic progressed.
[37] Some commentators have noted a distinct shift towards injecting heroin during the second wave of the epidemic. Pearson (1987) noted that some persistent users shifted to injection for financial reasons as it provides a stronger effect for less financial outlay.

individual is only likely to be `contagious' for a short period, perhaps up to a year. This is because after full-blown addiction occurs, "*the life pattern of the addict often changes; his whole energy becomes devoted to the acquisition of heroin. He may leave school, quit his job, but above all his associations will probably change. Once he is no longer in contact with his non-user friends, he can no longer expose them to heroin. Hence it is the new user not the confirmed addict who is responsible for the spread of new use*" (Hunt and Chambers, 1976). Secondly, people tend to have limited peer sets. So while the first user may introduce heroin to an entire social group, successors will have far fewer people to pass use on to, because everyone in the group will have already been exposed. The second user will only spread use to friends outside of the original group (ibid.).

These explanations of the spread of heroin remain theories. But regardless of the exact mechanism, the crucial result for this analysis is the underlying data that they purport to explain. These show very clearly that in actual epidemics the number of new users tends to rise very quickly but also to fall equally rapidly. This is evident in the graphs below showing the year of first use among heroin users in Chicago and Washington (Hughes *et al* 1972; Greene, 1974).

Figure 34: Year of first use among heroin users in Chicago

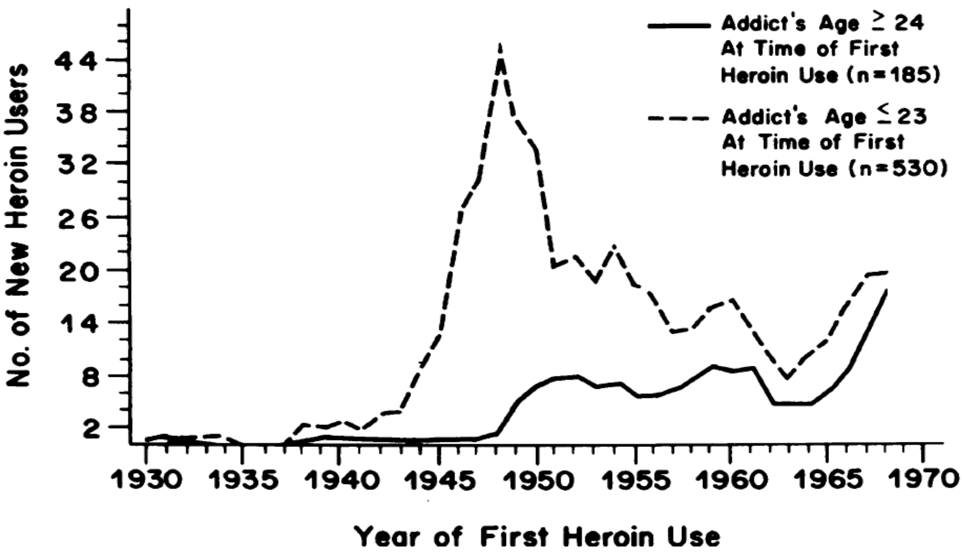
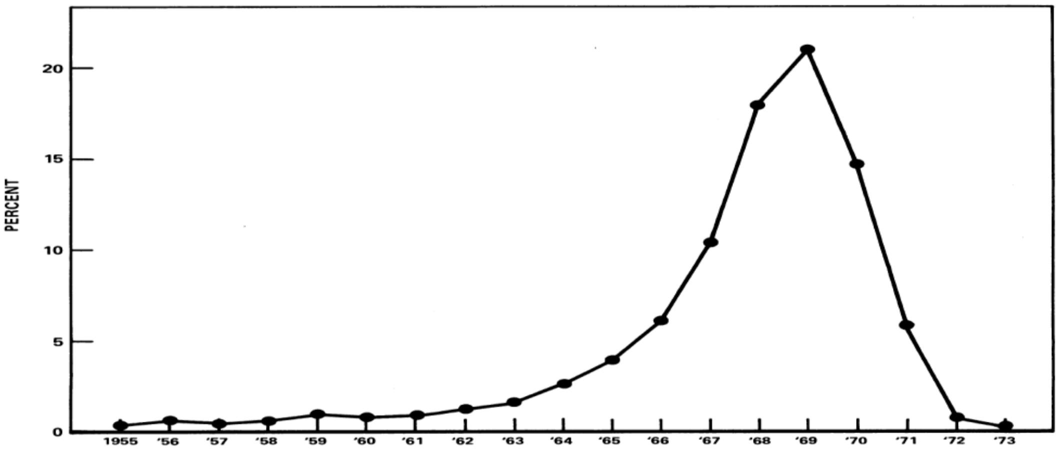


Figure 35: Year of first use among 15,000 heroin users in Washington



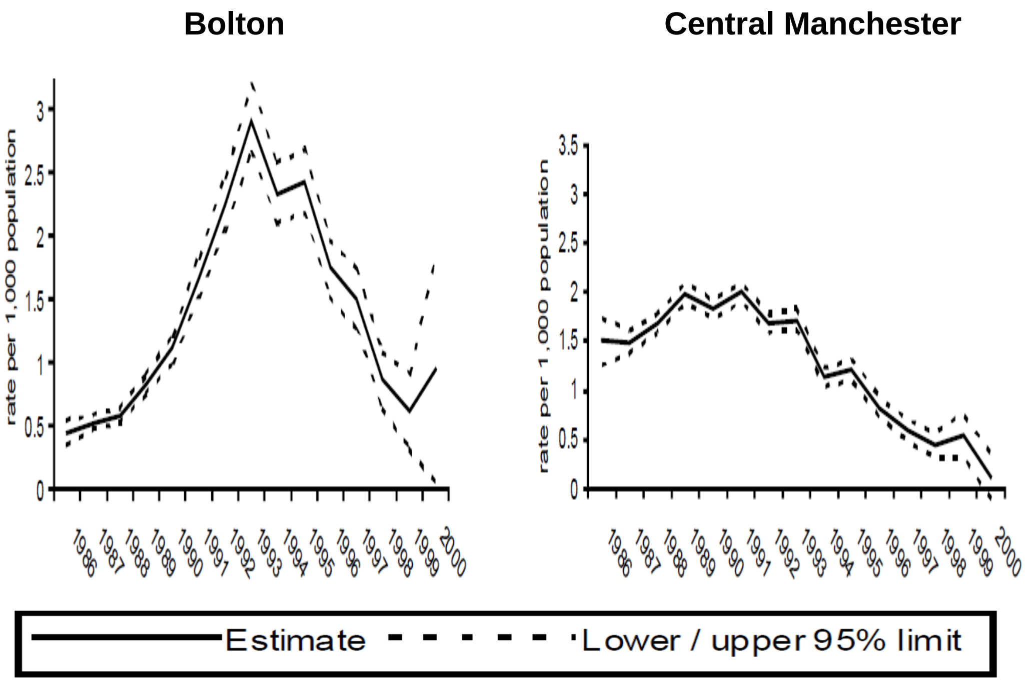
Source: Greene, 1974

Parker *et al* found exactly this pattern in the Wirral. Incidence decreased there almost as sharply as it had increased: from 800 new cases in 1984/5 down to 260 in 1986/7 and to less than 100 by 1990 (Parker, 2004).

Of course, what manifests as a spike at the local level may look quite different when aggregated up to the national level. Hunt and Chambers (1976) suggested that the US did not in fact have a single epidemic peak of heroin use, but a series of local peaks ranging from 1967 right through until the late 1970s. They also found a clear pattern to the geographic spread, which they labelled *macro-diffusion*. Similar to other types of social and technological innovation (they show that the spread of television sets followed a similar pattern), Hunt and Chambers found that heroin use tended to follow population density. Larger cities were affected first, followed by smaller cities, then large towns, small towns and finally more rural areas. In addition, there was also some suggestion, from the pattern of epidemics in the US, that once a localised area had an epidemic period it rarely had another one for at least 20 years – until there was a whole new susceptible youth population.

As with micro-diffusion, macro-diffusion also seems to have played a part in the UK epidemic. There is some evidence, in the few areas where data has been captured, that the epidemic spread from the most densely populated urban areas to the less populated surroundings. Some of this comes through in the work of Parker *et al* in the Wirral (Parker, 2004), but it is most clearly evident in a study by Millar *et al* (2001), which charts the progress of the epidemic through Greater Manchester and its suburbs. Using available data, they find that the peak of heroin initiation in central Manchester (population 2.7 million) occurred in 1988-90. From there the epidemic spread out to surrounding areas, peaking in 1992 in Bolton (population 139,000), and in 1995 in Bury (population 61,000).

Figure 36: Estimated trend in new heroin users in Bolton and Manchester, 1986-2000



Source: Millar *et al*, 2001.

Figure 36 shows another pattern seen throughout the Addicts Index data: the spike in opiate/crack use was generally sharper in areas with a single urban centre, like Bolton, rather than more sprawling urban locations like London and Central Manchester. Macro-diffusion offers a potential explanation: big cities have many urban centres of varying size, which would have been likely to have been affected by the epidemic at different times, giving rise to a more gradual rise and fall in opiate/crack use. But single urban-centre locations like Bolton would have seen a more focused impact.

Crack-cocaine

Crack-cocaine played very little part in the early stages of the epidemic. A study by Gossop *et al* (1994) found that before 1987, cocaine use was generally confined to powder cocaine ingested intra-nasally. But from 1987, a growing number of smokers of crack-cocaine began to emerge. Crucially though, and as was the case in the US, most evidence suggests that the majority of crack users were existing heroin users diversifying their drug use rather than totally new users. Two-thirds of the Gossop *et al* (1994) sample also used heroin, and a separate study by Strang *et al* (1990) in London concluded that "*we have found no evidence as yet of youngsters who have been directly recruited into use of crack without a considerable prior involvement in illicit drug use*." Their sample too showed considerable overlap with heroin – 60 of the 63 patients reporting crack-cocaine use also reported heroin use. Another study in Liverpool found almost identical results, concluding that: "*crack-cocaine injectors may represent a subset of heroin users rather than a distinct population*" (Sumnall *et al*, 2005). The Addicts

Index showed the number of notified cocaine addicts (it didn't separate out powder cocaine from crack-cocaine) increased by a factor of about 12 between 1983 and 1993, albeit starting from a very low level. It also agreed with other sources that crack-cocaine was often used as part of a poly-drug mix by the same addicts recorded in the heroin statistics. A paper by Hope *et al* (2005), which estimated that there were around 46,000 crack users in London in 2000/2001, summarised the available evidence aptly: *"...these estimates... suggest... crack use has increased in the population. However this does not imply that crack cocaine per se is responsible for a substantial increase in the number of problematic drug users in the population: there was substantial overlap with opiate use*."

The adoption of crack by some users probably still had an effect on the epidemic. Crack has a shorter high than heroin and whereas heroin users tend only to `score' two or maybe three times a day at most, crack purchases are often made far more frequently (Fagan *et al*, 1990). Clearly, this might alter any link with offending for both the user and supplier. The frequency of use means that crack markets yield a greater financial return to dealers, creating more competition, which in turn may lead to violence (ibid.). Links to offending are explored further in later chapters. For now, it is noted only that in the UK-context, it is probably wrong to talk about a *separate* crack-cocaine epidemic. It is also why, opiate and crack users are mostly grouped together and referred to as OCUs (opiate/crack users).

The second wave of the epidemic

Qualitative research suggests that the UK epidemic occurred in two distinct waves with a lull in the middle, and that (in a slight contradiction of the US model), some areas were affected during both waves (Parker, 2004).[38] So whilst parts of London (Hartnoll *et al*, 1985), the major Scottish cities (Haw, 1985) and other western regions of the British Isles (Parker and Gay, 1987; Fazey, 1991) appeared to follow Liverpool in having an outbreak in the early 1980s, much of the country remained relatively free of heroin until a second wave in the 1990s.

The evidence is probably too sparse to produce a definitive reason for this two-wave pattern. But two possibilities emerge. The first is that, like the first wave, the second wave was ushered in by the opening of a new supply route, this time through the Balkans (Parker, 2004). The second possibility is that heroin use escalates with unemployment, which, as we have seen, had two distinct national peaks, in 1987 and 1993.[39] Studies consistently reveal a relationship between drugs and unemployment throughout all stages of the heroin-using career. For example, boredom and lack of employment was the

[38] This depends, of course, on the geographic granularity. For the most part this review uses police force area level data, which is a high-level data source. It is possible that the US model is correct and different local areas within each force were hit in different waves.

[39] Analysis of unemployment rates by police force area reveals a general pattern for Northern and Western areas to have higher unemployment peaks in the 1980s and for Southern and Eastern regions to have higher peaks in the 1990s – see Table 9. This pattern is similar to that seen for the spread of the epidemic.

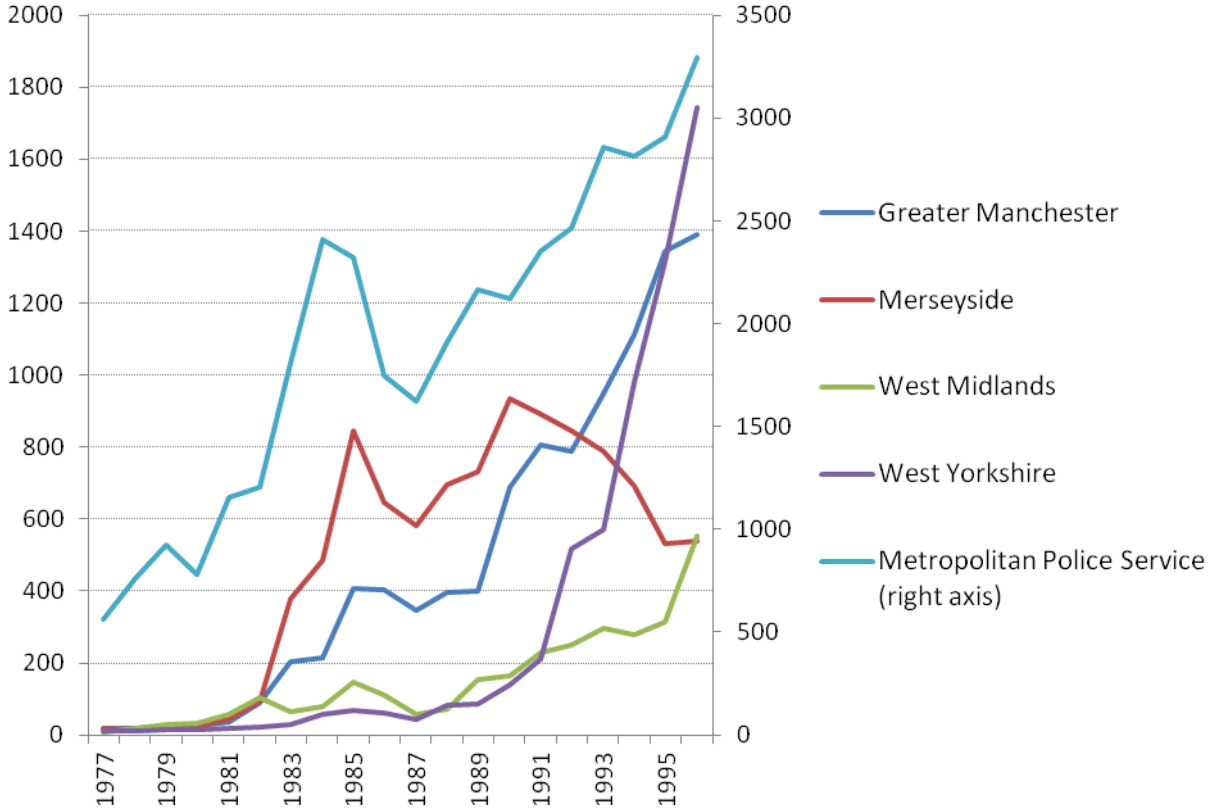
most cited reason for initiation in the Wirral sample (Parker *et al*, 1987). Also, evidence suggests that unemployed OCUs often escalate to daily use more quickly because workers tend to stick to a weekend-only pattern at least for a while (Pearson, 1987); and ex-users trying to stay off heroin tend to have more success when they have an occupation during the day (ibid., p181).

In charting the second wave of the epidemic, Parker (2000) identified three types of area: those that had a heroin surge during the first phase; those that only had a surge in the second phase, and those that had surges in both. For the first type of area, Parker cites Liverpool as the clearest example: "*the old heroin regions, particularly Merseyside, are not reporting significant new heroin uptake (in the 1990s) but instead are now the `kilo' wholesale depots for heroin distribution to new markets*" (Parker, 2000). Liverpool's absence from the second-wave of the epidemic may also be linked to its response to the first wave. Several studies show that Liverpool was one of the first areas to be affected by the epidemic but was also the first region in England and Wales to adopt a `harm reduction' approach to the problem. This focused particularly on methadone substitution treatment and referring arrestees to these services (O'Hare, 2007). One study claimed that in the late 1980s the city of Liverpool was responsible for about a third of all the methadone prescribed nationally (O'Hare, 2007).[40]

Data on opiate-related deaths, new users and heroin seizures – summarised in Figure 33 - also show support for the presence of two epidemic `waves.' There is an initial peak in all three indicators - opiate overdose deaths peak in 1982; and both heroin seizures and new users follow in 1985. Then there is a slight lull, before the indicators increase again, reaching a second, far higher peak at the end of the series. And the fact that some areas were hit in just one wave, while others got hit in both is also tentatively supported – see Figure 37 below, which compares the trend in new heroin users across the five police forces with the highest volumes of burglary (as of 1980):

[40] The same paper (http://www.canadianharmreduction.com/sites/default/files/Merseyside%20-%20Early%20Hx%20of%20HR%20-%202007.pdf) also claims that Merseyside's early adoption of a harm reduction approach also meant that "an HIV epidemic did not happen amongst injecting drug users in Mersey".

Figure 37: New heroin users in five police force areas



Source: Home Office, Addicts Index.

The geographical variation in trends evident in Figure 37 is important because it offers an opportunity to examine whether corresponding patterns are present in the crime data (see Chapter 5). Clearly, London (the Metropolitan Police Service) and Merseyside had the largest increases during the first wave of the epidemic, followed by Manchester. In contrast, West Midlands, and especially West Yorkshire seemed to remain largely unaffected by heroin in the 1980s. But this situation changed markedly in the second wave: Merseyside saw a decline in new users from 1990, while the number of new users in London and Manchester increased again, to an even higher level. West Yorkshire was affected substantially in the second wave along with West Midlands to a lesser degree. Figures 33 and 37 suggest that the second wave caused larger increases in heroin use than the first.[41] By the end of the period West Yorkshire has the highest number of new users outside London even though it seemed to have missed the first wave of the epidemic entirely.

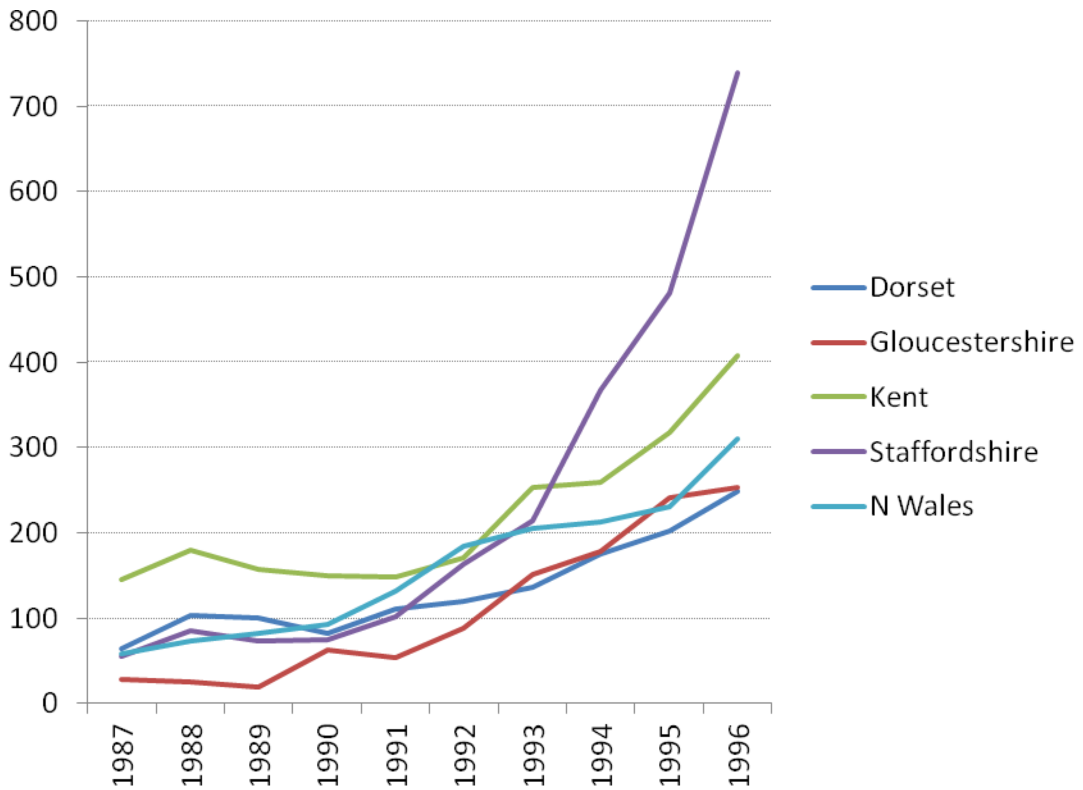
The data for all police force areas reinforces this point because Merseyside is actually the *only* police force area in England and Wales which had a

[41] Caution is needed here. While the Addict's Index data probably does identify whether areas were affected in the first or second wave of the epidemic, or both, it is important not to read too much into the exact timings or magnitude of the impacts. This is because the Addict's Index is in many ways reliant on the treatment response, as explained in the paragraph below.

declining trend in new heroin users by the early 1990s. According to the Addicts Index, almost every other police force area shows an epidemic-like rise in new users during the second wave. A few areas show trends similar to that of Manchester – they have increases in both waves. But many are like West Yorkshire in that they only appear to have been affected (and affected severely) in the second wave.

Other accounts of the epidemic also corroborate this picture. Parker *et al.* (1998) use an Addicts Index map of the UK in 1989 to show that large parts of England and Wales remained largely unaffected by heroin at this point.[42] But their map had changed by the mid-1990s, following a survey of police forces and drug action teams. With the exception of Staffordshire, Gloucestershire, Kent, Dorset and North Wales, all police forces in England and Wales that returned data reported having, or in Merseyside's case having had, a heroin outbreak. Furthermore, the Addicts Index data (see Figure 38) suggest that the survey responses from the exception areas possibly reflected a lack of awareness of a newly emerging epidemic, rather than no epidemic at all.

Figure 38: Trends in total heroin users reported to the Addicts Index, in the five forces that did not report an epidemic in Parker *et al*. (1998), 1987 to 1996



Source: Addicts Index

[42] Though see discussion of lag on Addicts Index data below.

Strang & Taylor (1997) analysed the Addicts Index data to show that the new users of the second period tended to be older and more male-dominated. Their analysis showed that the first wave was largely “gender neutral”, but that by 1993 there were three-and-a-half times as many new male users notified as female users. Parker *et al* (1998) also show that although many users began by smoking heroin, the second epidemic wave coincided with a transition towards injection, which may have exacerbated the crime impact.

In summary then, whilst the first wave seemed to affect Merseyside and a few other, mostly Western, regions, by the time of the second wave, the heroin epidemic was a national phenomenon.

The peak of the epidemic

Paradoxically, what happened next is almost the hardest part of the story to discern. The Addicts Index was still showing a rise in new and total users in 1996, but as noted this is likely to lag the true situation by at least two to three years, and after 1996 the series was discontinued. There was then no standardized measure of OCU volumes until the annual estimates (Hay *et al*., 2006; 2012) of the mid-2000s.[43] These showed a stable or falling trend in total OCUs. On their own then, these series suggest that the peak was somewhere between 1993 and 2004 but do not allow for more precision than that.[44]

Interestingly, Parker *et al*’s 1998 study of the second wave of the epidemic was the last paper that could be identified that talked about *new* outbreaks of heroin use in England and Wales. From the perspective of the Hunt and Chambers (1976) model this is not surprising. The logic of micro-diffusion would suggest that incidence levels rise *and fall* very quickly and the evidence from macro-diffusion suggested that once all susceptible individuals within an area had been `exposed’ to the epidemic, the area tends not to have another epidemic for at least a generation - once the memory of the previous heroin problem has diminished amongst the youth population.

De Angelis *et al*. (2004), using a variety of models that work backwards from drug overdose deaths to estimate the year of first use, concluded that the peak in new users probably occurred around 1996 in England and Wales.[45]

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[43] Note that the Hay et al estimates are for OCU prevalence in England only. But, according to the Addicts Index, in 1996 (the last year that the Index collected data) only 2% of OCUs resided in Welsh police force areas. So this is unlikely to change the trend in a major way. See also the assumption log and sensitivity analysis carried out in relation to the Hay *et al* estimates in Appendix 7.

[44] This analysis does not graph the number of OCUs over time using its two main data sources – the Addicts Index and the Hay *et al*. estimates. Doing this would have made it appear that the numbers of OCUs must have continued to increase dramatically during the gap between the two series. The evidence presented in this paper (particularly the age breakdown of the current cohort) suggests that this conclusion, which may have led many to reject opiate/crack use as a partial cause of the crime drop, is almost certainly wrong. The difference in magnitude between the two series is due to the under-counting of the Addicts Index, not because the trend continued to increase. Figure 67 hopefully gives a better view of the true trend in OCUs. It is an attempt to model this trend. However, please note that this modelling is exploratory and encompasses a number of necessary assumptions that are open to challenge.

[45] A study by Sutton *et al* (2004) also looks at incidence levels nationally, but only of injecting users. It concluded that initiation peaked in the early 1980s and remained stable through to the mid-1990s

Other local-level estimates suggest an even earlier peak. Parker *et al* (1988) find declining incidence in Merseyside from around 1986, and Millar *et al* (2001) find that the central and most highly-populated regions of Manchester were seeing falling numbers of new users by the early 1990s, see Figure 36. Another study by Hickman *et al* (2001), using self-reported age of initiation of drug users attending treatment, concludes that incidence in the South-East of England, one of the later areas affected by the epidemic (London excepted) peaked in 1996/97. A paper by Sweeting *et al* (2009), which estimated the number of *former* injecting drug users in the population in 2003, found that a very small proportion started using post-1998. These results tally with the modelling section of this paper (see Chapter 6), which finds that the path of the epidemic that best fits current data involves a peak in incidence around 1995 with a sharp fall from 1998.[46]

If that is the case, then one aspect of the epidemic, the in-flow of new users, was essentially over by the end of the 1990s. That this is not the end of the overall story is due to the relationship between new users (incidence) and *total* users (prevalence). The relationship between incidence, prevalence and the rate at which OCUs exit the population (either by quitting or dying) is examined in detail in Chapter 6, and interested readers are referred to the evidence presented there. But a few of the most salient facts are useful here.

It is clear, for example, that whilst some users manage to quit opiate and/or crack-cocaine use relatively quickly, a proportion continue to use these drugs for many years (Hamilton *et al*, 2009; Darke *et al*, 2003). This means that the peak in *prevalence* will be later than the peak in *incidence*. How much later depends on the proportion of users that manage to quit early and the proportion that have long drug-using careers. This remains a matter for debate. Some studies suggest that a greater number of users (even regular users) quit within 1-2 years of initiation than in subsequent years (Kaya *et al*, 2007; Sweeting *et al*, 2009), while other studies suggest that the cessation rate is more or less constant across the drug-using career (see for example Heyman, 2013). The outcome of this debate has important implications for judging the `shape' of the epidemic from the peak onwards. If a higher percentage of users quit quickly, the peak will be sharper and closer to the

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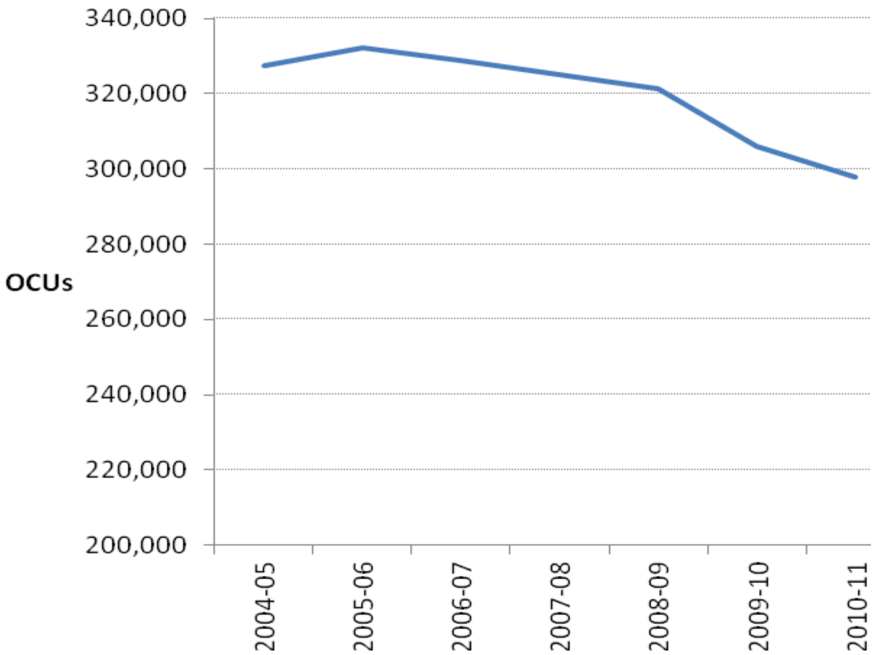
before declining. Though this pattern does not seem to agree with much of the rest of the evidence, it does at least tally with the conclusions presented here in the sense that incidence was almost certainly falling by the late 1990s.

[46] Indeed, one of the key conclusions of this analysis is that the dates for the entire epidemic may have been misjudged slightly due to the lag on our primary datasets. For example, figure 37 doesn't suggest an incidence peak in Merseyside till around 1990, yet Parker's survey data (which included non-treatment sources) finds that incidence was probably declining from 1986 (in the Wirral at least). Similarly, figure 37 suggests that incidence was still rising in Greater Manchester by 1996, yet Millar et al (2001) using a more robust method, find that incidence in the most population dense areas of Manchester was falling from about 1989. Recall that opiate users were notified (and hence appeared in the index) mostly via GP and treatment sources, meaning that notifications would have been likely to increase with the provision of treatment services. This may help to explain why the number of new users seems to increase so much more dramatically in the second wave of the epidemic compared to the first; by this time, treatment services had expanded so a greater proportion of users would be likely to be notified (even, perhaps, some who had actually initiated in the first wave). In other words, the lag on the Addicts Index data is probably quite considerable but also potentially variable across time *and* area.

incidence peak – as it is in the modelling work of Rossi (2002), which uses data from the Italian epidemic.

Despite this disagreement, studies concur that once OCU careers are well established, cessations rates are low, in the order of 5-12% per year, though they are often punctured by periods of attempted cessation (sometimes aided by treatment) and relapse (Calabria *et al*, 2010, Galai *et al*, 2003, Termorshuizen *et al*, 2004; De Angelis *et al*, 1996).[47] This means that we can say with some certainty that a few years on from the peak, the decline in the OCU cohort is likely to become quite gradual. This is more or less the picture we get from the Hay *et al* (2012) estimates, see Figure 39 below, which use a capture-recapture method to calculate prevalence from 2004/05.

Figure 39: Estimates for the size of the OCU population in England[48]



Source: Hay *et al*, 2012

Figure 39 suggests that by the mid-2000s OCU prevalence had reached around 330,000, a figure that is corroborated to some extent by data from the Drugs Data Warehouse.[49] It also suggests that numbers were gradually

[47] Note that these figures should not be directly compared with the 2.5% rate of reduction implied by the Hay *et al* estimates for prevalence. The latter figure is the net effect both of those who exit the population *and* those who enter it in any given year.
[48] Note that the Hay *et al* estimates are only for England, not England and Wales. However, in the last year that the Addicts Index measured total heroin users (1996), Wales only had 572, around 2% of the total for the total for England which had more than 27,000. Given that adding this percentage on to the totals in the Hay et al estimates would not raise these totals out of their confidence intervals, the decision was taken not to try and adjust the results for Wales in the modelling in Chapter 6. If anything this makes the estimates in that chapter more conservative.
[49] This latter figure is corroborated to some degree by the Drugs Data Warehouse (DDW), a Home Office database that has linked, anonymised information for over one million drug-misusing individuals identified either within the Criminal Justice System and/or through contact with drug treatment services between 1 April 2005 to 31 March 2009. It identifies 306,000 unique individuals

reducing at an average rate of about 2.5% per year.[50] The apparent peak in 2005/06 can probably be ignored for several reasons. Firstly, the rise from 2004/05 to 2005/06 is not statistically significant, though the downward trend from the start of the series to the end is. Secondly, as Frischer *et al* (2009) argue, because the Hay *et al* estimates are based largely on treatment datasets they may lag the true situation slightly. Treatment provision expanded significantly in the early years of the series (from about 2003-2005) and waiting lists reduced considerably. Arguably then, by 2005/06 there would have been a lot more treatment seekers captured, which may have created a slightly artificial rise in the estimates.

Other studies suggest the peak in total users occurred much earlier. Frischer *et al* (2009), using longitudinal data from the General Practice Research database, suggest that both incidence *and* prevalence of OCUs under the age of 25 declined from 1998.[51] Godfrey *et al* (2002) estimated the total number of injecting drug users at 405,000 in 2000, markedly higher than the later Hay *et al* estimates. Though Godfrey *et al* used a less robust methodology to reach their figure, there is a logic to their higher estimate. If there were about 330,000 OCUs in 2004/05, but the peak occurred several years earlier, then at the peak the total number of OCUs must have exceeded 330,000.

Age effects and the current cohort of heroin/crack users

Perhaps the clearest sign that the epidemic was past its peak by the mid-2000s comes from the cohort's age data. Both the Hay *et al* (2012) estimates and the DDW agree that by the late 2000s, the OCU population had an average age of around 35. Yet the average age of initiation, as shown by several studies (from different time periods), is around 18-20; and only about 3% of OCUs start using opiates or crack-cocaine over the age of 35 (Donmall

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over that period who either attended treatment services for heroin/crack addiction or tested positive for opiates/cocaine following arrest or were identified as an opiate/crack user by probation services. Though we'd expect some of these unique individuals to exit the OCU population through the period (and hence for an annual count to be slightly lower), we would also expect a degree of under-counting on the DDW due to the difficulty of matching all individuals to each data source and the fact that some OCUs may not appear on any of these datasets. The fact that the DDW identifies over 300,000 unique individuals from treatment or CJS data sources is extremely important for the modelling later in this paper. One of the key uncertainties of that process involves *extrapolation.* That is, our offending rates for OCUs generally come from treatment or arrestee samples, and it has been argued that extrapolating offending rates from this group to the whole population is wrong because OCUs who do not appear on treatment or CJS datasets may have lower offending rates (Stevens, 2007). The results from the DDW show that virtually the entire OCU population suggested by the Hay et al (2012) estimates can be accounted for by individuals who show up on treatment or CJS datasets, which suggests that any extrapolation error may be minimal. Note that this does not mean there isn't a population of OCUs who commit less crime and don't seek treatment; it just means that if such a population exists it is either relatively small or exists *on top of* the 300,000 or so OCUs estimated by Hay et al (2012) and the DDW.

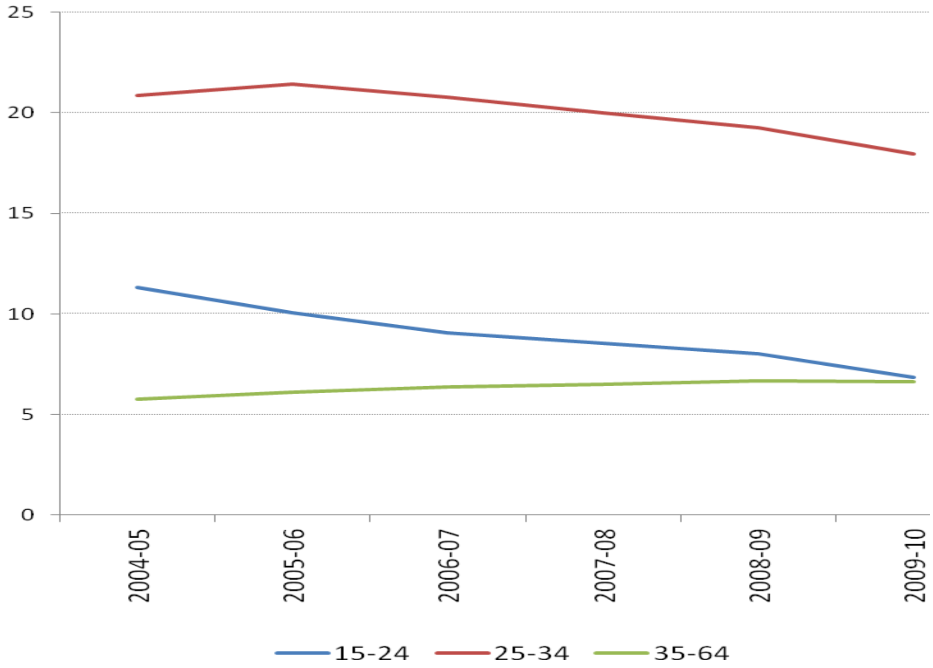
[50] Note that we would expect the fall in the entire cohort to be smaller, in percentage terms, than the cessation rate, because, although incidence rates had probably declined hugely by this point, they will not have gone to zero.

[51] Note that even this measure is likely to be lagged as users may take some time before reporting their use to a GP.

& Jones, 2005). Thus, the average age of the population in the late 2000s can be taken as a sign that the epidemic was well past its peak at that point.[52]

This conclusion is further strengthened by the presence of a `cohort' effect in the data, see Figure 40:

Figure 40: OCUs in England per 1,000 population, by age[53]



Source: Hay *et al*, 2012.

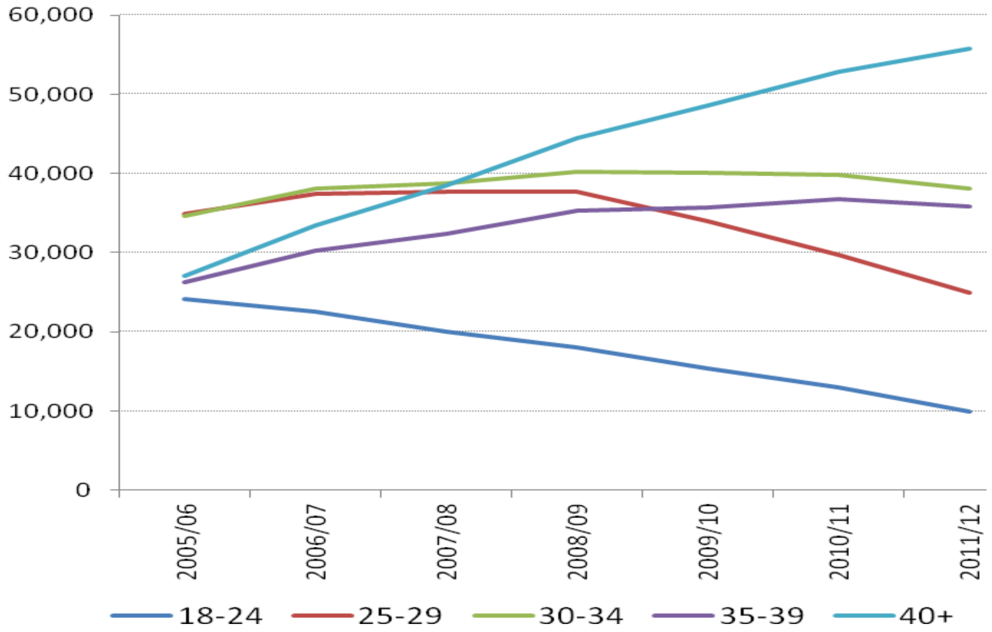
The chart shows that the number of young users (aged 15-24) fell consistently through the series, whereas the number of 25-34 year-olds had one year of increase before falling, and the number of over-35s actually increased through this period. It seems unlikely that this was a result of greater initiation of older users given the evidence on age of initiation and its apparent consistency over time. More likely is that this pattern reflects the movement of existing users through the age ranges over time. i.e. an ageing drug-using population.

This `cohort effect' is also evident in the trends in the number of new presentations to treatment; and in the trends for drug deaths, see Figure 41:

[52] Modelling revealed that it is just about possible to have an incidence peak in the mid-to-late 1990s, a prevalence peak in the mid 2000s *and* an average age of over 30 at that point, but only if the exit rate for the OCU population was unfeasibly low. This is explored further in the Modelling section, see Chapter 6.

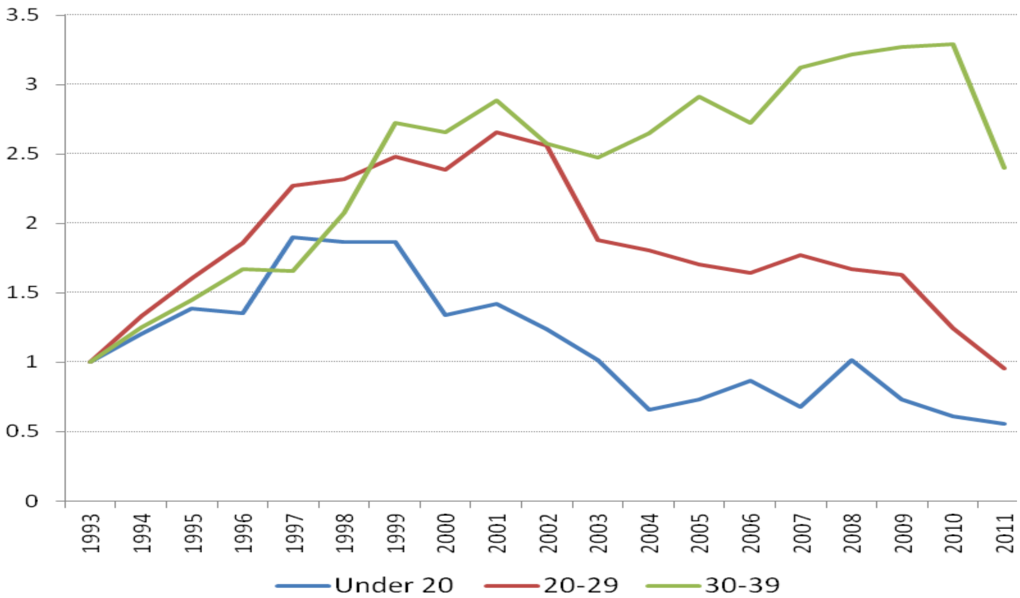
[53] Note that these trends should also be treated cautiously, as all the point estimates have confidence intervals around them. However, the reduction in 15-24 year-olds and 25-34 is statistically significant between 2004/05 and 2009/10 as is the rise in older users. And of course, the triangulation with the other sources might also give us some confidence that the cohort effect is real.

Figure 41: Total treatment presentations for opiates/crack, by age



Source: http://www.nta.nhs.uk/uploads/statisticsfromndtms201112vol1thenumbersfinal.pdf

Figure 42: Age-specific mortality rates for deaths related to drug misuse, males, England and Wales, 1993–2011 (indexed to 1993)[54]



Source: Deaths related to drug poisonings, England & Wales, 2011 (ONS)

Figure 42 shows that trends in treatment seekers have fallen most sharply amongst the youngest group (18-24s), followed by the 25-29s. By contrast, the older age groups have seen rises over the period with the over-40s seeing the biggest increase, such that in 2011/12 they made up by far the biggest

[54] Drug misuse deaths cannot be taken as proxy measure of prevalence due to the fact that the relationship increases with age. Thus, whilst it is likely to be true that a greater volume of OCUs is likely to give rise to a greater number of `drug misuse' deaths, a smaller but more aged OCU population might actually have a far greater drug misuse mortality rate.

group of new treatment seekers. Similarly, Figure 42 shows a rise and fall in drug misuse deaths occurring at different times for different age groups. Again, the younger age groups start falling earlier. Taken together, these charts suggest not only that the peak of the epidemic must have occurred well before the mid-2000s, but also that today's OCU population is still dominated by those who initiated use in what might be termed the `epidemic period'.

The price of heroin/crack

Like the size of the OCU population, the price of heroin/crack probably varied markedly through the epidemic period. As with virtually all areas relating to illicit drug consumption, data is sparse and imperfect, but some studies have pieced together what is available and attempted to draw out trends. For example, Farrell *et al* (1996) collected UK data into a series from 1983 to 1993 (with some years where data was unavailable), see Table 3 below:

Table 3: UK Heroin and Cocaine Prices (Street price is in US$ per gram and Wholesale price is in US$ per kilo)

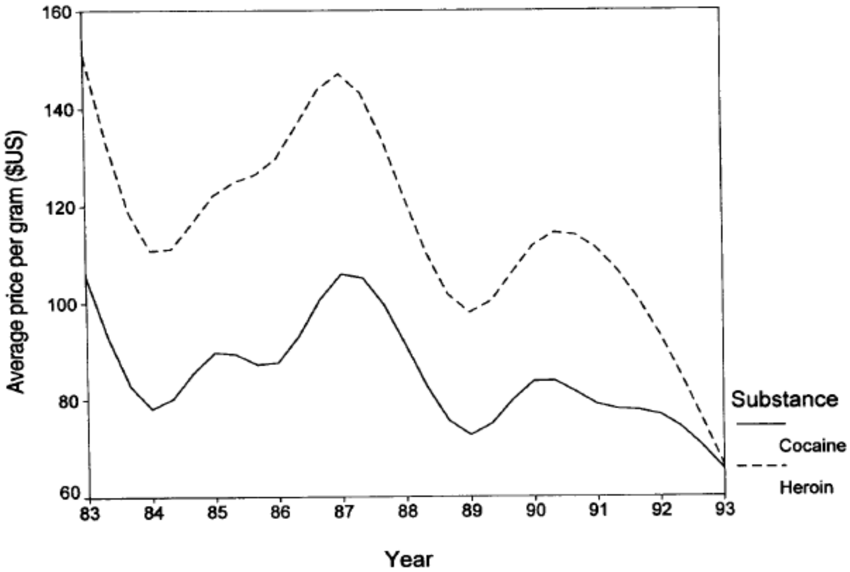
	Heroin		Cocaine	
	Street	Wholesale	Street	Wholesale
1983	122	45900	107	53550
1984	95	40500	81	43875
1985				
1986	113	26021	110	39716
1987	128	37545	128	38962
1988	143	40557	118	43738
1989	114	31675	108	46879
1990	120	41318	100	36653
1991	105	32252	93	
1992			49	
1993	94	30247	86	30247

Source: Farrell *et al*, 1996.

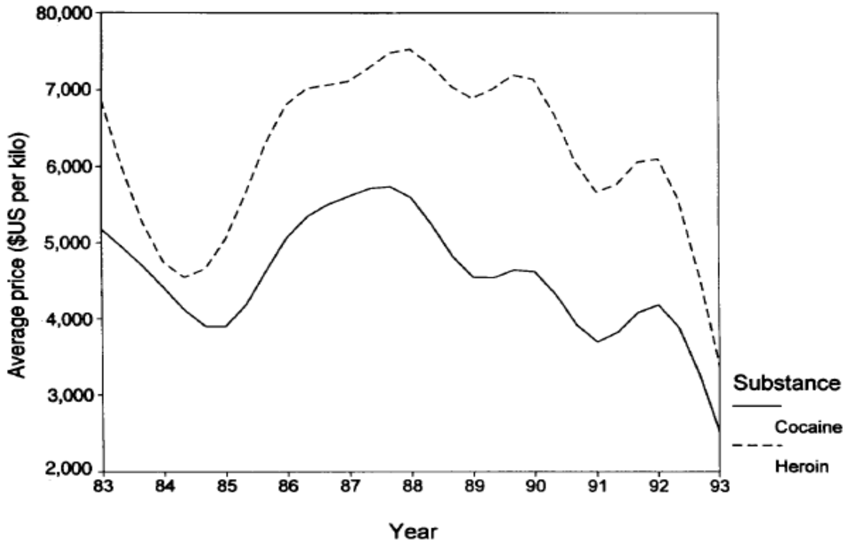
It is difficult to discern clear trends from this data, but the paper also produces European-wide trends for the street and wholesale price of heroin and cocaine. These are shown in Figure 43 below:

Figure 43: European trends in the price of heroin and cocaine

Street price



Wholesale price



Source: Farrell *et al*, 1996.

Overall, this data suggest that prices probably peaked around 1987/88, fluctuated through to 1992 and fell sharply from 1993. After 1993, there is tentative evidence that UK prices fell at a more gradual rate. The Independent Drug Monitoring Unit has price data for heroin from 1995, which show that heroin prices decreased gradually and steadily from 1995 through to around 2002, but then stabilised at £40-£60 per gram through to 2010/11. This is broadly consistent with the trend contained in the report by Matrix Knowledge Group (2007), which was generated using data from user interviews.

It is difficult to determine what effect these price fluctuations might have had on drug consumption and drug-related crime. Evidence demonstrates that even dependent drug users are responsive to price and that as prices rise consumption – on the whole - is likely to decrease (see for example Saffer &

Chaloupka, 1995; Gallet, 2013). Of course, even if changes in price drive changes in consumption, the effect on crime is ambiguous. If prices rise, drug users may commit more crime in order to finance the same level of consumption. But if the price rise prompts a decrease in consumption or even cessation then aggregate crime could fall. As Bretteville-Jensen (2006) points out, price changes could have very different effects at different stages in a drug-using career. Low prices might tempt more individuals into initiating and hence increase aggregate crime, but for established users it could result in less crime if less illegal income is required to finance a constant-level of consumption. Indeed, studies that have looked at the relationship between heroin/crack prices and crime have come to mixed conclusions. Silverman & Spruill (1977) use US data and a time-series model to estimate that a 50% increase in heroin price results in a 14% increase in property crime, while Desimone (2007) find the opposite relationship for crack.

Just to complicate things further – it may be the case that supply-shocks in drugs markets are dealt with via changes to drug purity rather than price.[55] So arguably price-purity data would be needed to definitively establish a relationship with crime. But this has not been identified for the early epidemic periods. Overall then, it is very difficult to draw any firm conclusions from the data on drug prices, though clearly, it is at least possible, that the large drop in prices that seemed to occur in Europe around 1993 could have been a factor in the sharp recorded crime falls seen at that time.

The criminal justice system response

Figure 25 showed that there was an increase in the total prison population between 1993 and 1998. It rose by around 50% over this period meaning that around 24,000 more individuals were in prison in 1998 than at the crime peak in 1993 (MOJ, 2013). Table 4 shows a breakdown of the sentenced prison population (it does not include prisoners on remand) from 1990 to 2013. It suggests that many of those newly incarcerated during the period of the crime turning point may have been OCUs, as there were marked increases in most types of offences between 1990 and 2000, including those like burglary and theft that are associated with heroin/crack (see Chapter 4).

[55] This seems to be what has occurred in the recent period. The European Monitoring Centre for Drugs and Drug Addiction (EMCDDA) reported that a small group of European countries, including the United Kingdom, appeared to have experienced a reduced supply of heroin in 2010/11. Data from the Serious and Organised Crime Agency (the work of which is now being done by the National Crime Agency) suggest however, that while this affected wholesale heroin prices markedly, street prices remained relatively stable and purity fell instead.

Table 4: Sentenced prison population by offence groups, 1990 to 2013, England and Wales [56]

	1990	1995	2000	2005	2010	2013	Increase 1990-2000	Increase 1990-2013
Violence against the person	7,477	8,781	11,217	15,178	20,247	19,473	50%	160%
Sexual offences	3,018	3,668	5,090	6,185	9,304	10,540	69%	249%
Robbery	4,052	5,372	6,353	8,378	8,834	8,873	57%	119%
Burglary	5,885	5,953	8,982	8,082	6,857	7,073	53%	20%
Theft and handling	3,042	3,729	5,044	4,126	3,850	4,500	66%	48%
Fraud and forgery	795	1,167	1,016	1,454	1,544	1,320	28%	66%
Drug offences	2,829	4,256	8,473	10,661	11,064	10,175	200%	260%
Motoring offences	na	1,678	2,328	2,163	931	723	na	na
Other offences	3,280	2,628	3,723	5,289	7,353	7,625	14%	132%
Offence not recorded	3,148	1,631	866	664	887	479	-72%	-85%
All offences	33,526	38,863	53,092	62,180	70,871	70,781	58%	111%

Sources: Data for 1990 to 1993: Prison Statistics England and Wales (1999), Table 1.7 (motoring offences were included in `other offences'). Data for 1994 to 2004: Offender management caseload statistics England and Wales 2004, Table 8.2. Data for 2005 to 2013: Annual prison population (2013), Table A1.3b.

That some of the newly incarcerated were OCUs is supported by a study of newly remanded males at a prison in north-east England at the time. It found that 70% reported a history of illicit drug use and 57% had used illicit drugs during the year prior to prison; 44% were recent users of amphetamines, a third opiates and 15% cocaine (Mason, Birmingham & Grubin, 1997)

It is possible, then, that there may have been a stronger prison effect on crime at this point compared to outside of the epidemic period. Given the frequency of offending reported by some OCUs, even if the custodial sentences were relatively short, they may have prevented some crimes due to incapacitation. And the greater likelihood of receiving a custodial sentence *might* also have acted as a deterrent for a proportion of the OCU population, which was probably close to its maximum volume at this time.[57]

The interaction between heroin/crack use and changes in the prison population may have cut both ways however. A survey of prisoners in 1995 showed again the high level of drug use among prisoners, but also the high percentage of prison drug users who initiated their use in prison, particularly

[56] These figures have been drawn from administrative IT systems which, as with any large scale recording system, are subject to possible errors with data entry and processing. Due to differences in recording practices over time, a time series of this data broken down by sentenced and remand populations is not available. Note also that the increase in prisoners sentenced to custody for drug offences was affected markedly by increases in sentence severity, the re-classification of cannabis and the introduction of a three strikes law, mandating a longer sentence for the third offence.

[57] Generally evidence suggests that improving the swiftness and certainty of punishment is more effective than increasing its severity (Durlauf and Nagin, 2010). But some studies have found effects, for example, Helland and Tabarrok, 2007.

for heroin (Boys *et al*, 2002), see Table 5 below. It is possible that these initiation rates, which have reduced in the years since,[58] partly reflect the evidence on the peer-to-peer spread of heroin presented earlier. That is, as more heroin users appeared in the prison system, it is possible that they spread use to new initiates in a similar way to that which occurred in a community setting. This might have implications for the way in which heroin users are housed in relation to other prisoners, though further research in the prison context would be required to confirm this.

Table 5: Results of a 1995 survey on drug use and initiation in prison

Drug Type	Frequency (% of total)	Ever used in prison (% ever users)	Initiated use in prison (% ever used)	Initiated use in prison (% of those used in prison)
Cannabis	2,411 (76.7)	1,538 (63.8)	154 (6.4)	10.0
Amphetamines	1,529 (48.7)	216 (14.1)	36 (2.4)	16.7
Cocaine/crack	1,442 (45.9)	351 (24.3)	134 (9.3)	38.2
Heroin	1,203 (38.3)	743 (61.8)	318 (26.4)	42.8
Injecting drug use	818 (26.0)	130 (15.9)	33 (4.0)	25.0

Source: Boys *et al*. 2002

Summary of the key points from this section

1) Sparked by an increase in supply, heroin use increased dramatically in England and Wales from the late 1970s and early 1980s.

2) Data show that, within local communities, the number of new users tended to increase very quickly but then decrease just as quickly. A likely explanation is that use spread rapidly via friend networks and dried up once everyone in these networks had been `exposed'.

3) At the macro-level, the epidemic probably occurred in two waves and broadly with a West-to-East dynamic. In other words, there was marked *geographical variation* in both the ordering and severity of the epidemic across police force areas.

[58] The 1997 Psychiatric Morbidity Survey reported a similar figure (30%) for the proportion of heroin users in prison who initiated use in prison. More recent figures suggest that this proportion has declined however. The Surveying Prisoner Crime Reduction longitudinal cohort study of prisoners, covering interviews with prisoners sentenced in 2005/6, found that 19% of heroin users said they started use in prison. The same study also found that a third of respondents admitted using Class A drugs following release and these individuals were significantly more likely to re-offend within a year compared with those who did not report using Class A drugs following release (76% versus 43%).

4) Some users diversified into crack use alongside heroin use as their drug-using career developed, but there was no evidence of a separate crack epidemic as there was in the US.

5) Though the peak in new and total users cannot be determined with absolute certainty, there were no reports of new outbreaks from the late 1990s onwards and the current age of the OCU population also suggests that the peak is likely to have been before 2000.

6) The current OCU population is both declining and ageing, meaning that it is probably still dominated by the cohort of users who began their opiate/crack careers during the epidemic period. It also means that the number of new users has probably tailed off markedly in recent years.

7) Heroin/crack prices through the epidemic period are difficult to discern precisely and are complicated by the fact that street-level purity can vary too. However, there does seem to have been a big fall in prices that took place alongside the fall in crime.

8) The increase in the prison population that occurred in the mid-1990s probably incapacitated a number of OCUs (and possibly deterred others), hence may have affected crime levels, alongside other factors. However, prison may also have contributed to the longevity of the epidemic as a number of individuals seem to have initiated heroin use in prison at that time.

Chapter 4: The relationship between opiate/crack use and crime

Central to the analysis in this paper is the question of whether opiate/crack use causes acquisitive crime. To assess this, we conducted a non-systematic review of studies that surveyed or collected data on this issue. In total we found 36 relevant studies and these have been summarised along with their conclusions in Appendix 4. Without exception the studies showed that, *in aggregate*, cohorts of opiate and crack-cocaine users commit a very high volume of offences, whether they are drawn from treatment-based settings, criminal justice system settings or community-based settings; and whether they come from England and Wales or another nation. More detail can be found in Appendix 4 but a few bullets should serve here:

- More than half (55%) of all burglary offenders identified in the Wirral during the epidemic period were known heroin users, and heroin users were over-represented in all crime types tested except criminal damage (Parker & Newcombe, 1987)

- A sample of 46 London-based heroin users in the 1980s, drawn from treatment and prison sources, admitted to aggregate spending of £23,000 a week on heroin, yet their total legitimate income was just £2,100 per week. (Jarvis & Parker, 1989)

- In a study of 210 drug users in Scotland recruited from community settings, opioid users admitted committing theft on an average of 37 days per year, but for those who were injecting the figure rose to 108 days per year (Hammersley *et al*, 1989).

- A sample of 1075 treatment seekers from across England and Wales recruited for the National Treatment Outcome Research Study (NTORS), 87% of whom were heroin users, self-reported 27,787 acquisitive offences in the previous three months. (Stewart *et al*, 2000)

- From a sample of 384 arrested heroin users in Baltimore, 243 males had on average committed more than 2000 offences per individual per year for the previous 11 years (Ball *et al*, 1983).

- A cohort of just 356 heroin users recruited from community settings in Miami self-reported more than 118,000 crimes in the previous year (Inciardi, 1979).

- A study of 1,828 defendants testing positive for specified class A drugs (mostly opiates/crack) between May 2004 and July 2005 revealed that all but 18 had previous convictions; 1,089 had more than 50 convictions and the mean number of total convictions was 170. The mean number of years between first conviction and appearance in the study was 14 years (Hucklesby, *et al*., 2007).

- A meta-analysis of 30 studies showed that odds of offending were between 2.8 and 3.8 times greater for drug users than non drug users (Bennett *et al.*, 2008).

The studies above collected data on different types of crimes in each case, but there was general agreement that apart from drug dealing (and prostitution amongst female OCUs), the most common crimes committed by OCU cohorts were acquisitive crimes. For example, one study of the England and Wales prison population in 1997 found that 53% of male sentenced prisoners and 61% of male remand prisoners reported a measure of dependence on drugs in the year before prison, and that these individuals were statistically significantly more likely to have been incarcerated for an acquisitive offence (Singleton *et al*, 2003). The studies also tend to agree that the most common acquisitive crime committed by opiate/crack users is shoplifting. For example, of the 27,787 acquisitive crimes admitted to by the NTORS sample (mentioned above), 21,479 were shoplifting. This is equivalent to an average of 80 shoplifting offences per individual per year.

In addition, all studies that examined the distribution of offending within the OCU cohort agreed that, as with all other types of population cohort, offending amongst OCUs is markedly skewed. A few individuals commit the bulk of offences. Or to put it another way, many OCUs commit little or no crime.[59] For example, in NTORS three quarters of the crimes were committed by 10% of the sample and 50% reported no acquisitive crime at all (a fact that was backed up by looking at official records).[60]

The studies are also unanimous in finding that a high proportion of the OCUs offending at high rates began their criminal careers *before* they started using opiates and/or crack, which implies that opiate/crack use did not cause the *onset* of offending. However, this point needs to be qualified in two ways. Firstly, though this may be true of the majority of users, there is good evidence that some individuals did start offending in line with or *after* the onset of regular heroin crack use, implying that these drugs could have caused offending onset. Furthermore, estimates for the size of the latter group vary depending on when the study was carried out. Generally, cohorts from earlier in the epidemic seem to contain greater proportions of OCUs whose criminal career commenced at the same time, or *after* their drug use, whereas later, more recalcitrant cohorts tend to show the opposite pattern. For

[59] And, as explored in the modelling section, this point becomes even starker if the category is restricted to `acquisitive crimes.' Many OCUs seem to be able to fund their drug use through a combination of legal means and dealing.

[60] This is a crucial fact for the modelling of OCU crime carried out later in this paper. Without exception studies find that there are always a few OCUs, within any given cohort, who commit an incredibly high volume of crimes. This drags up the average offending rate for the cohort as a whole and means that the average is a poor predictor for the majority of OCUs (who will have far lower offending rates or commit no crime at all). But the fact that across time and geography there consistently seems to be these high-rate offending outliers, means that the average offending rate *can* be applied to aggregated cohorts of OCUs over time, which is what is done in this analysis.

example, the Wirral studies find that the majority of heroin users commenced offending *afte*r heroin use[61]; but studies like Pudney (2002), which used a sample from 1998/99, found that whereas the average age of heroin initiation was 17.5, the age of first offence was just 14.5. There is also tentative evidence to suggest that those who offend regularly before heroin/crack initiation generally have a higher set of other crime risk factors (like conflicted families, social disadvantage etc) and go on to have a longer criminal career (Kaye *et al*, 1998; Byqvist and Olsson, 1998; Nurco *et al*, 1989). But importantly these studies also find that, for those who only become regular offenders *after* first heroin use, though their career may be shorter, their offending levels may have been just as high during periods of regular use; a conclusion echoed by the Wirral findings (Parker & Newcombe, 1987).[62]

To summarise then, at a cohort-level, OCUs commit a lot of (particularly acquisitive) crime, *but* opiate and crack use clearly does not lead inexorably to prolific offending; and similarly it is not the case that the `typical' OCU will also be a prolific offender. It is also the case that many OCUs with the longest criminal careers began offending before taking opiates/or crack. It is perhaps for these reasons that the studies disagreed on one thing: whether drug use was the primary cause of these high offending levels. On this, the studies were split roughly half-and-half, with as many tending towards the conclusion that opiate/crack use was a correlate of high offending, rather than a cause.

In theory there are three ways to explain the fact that cohorts of OCUs seem to commit very large amounts of crime. Either drug use causes crime; or crime causes drug use; or some third factor causes both. In a 2009 paper Bennett and Holloway looked at the first two of these options. They summarised all the different ways in which 41 offenders reported that drugs (including alcohol) were involved in their offending. They identified 77 different drug-crime connections (incidences where offenders self-reported a link between a particular drug type and a particular crime type) and they then coded these to either drugs-cause-crime explanations or crime-causes-drugs explanations. The main mechanisms are summarised below.

[61] Importantly – the measure used here is official records of offending, not self-reported offending. It is likely that self-reported offending would have told a different story. But self-reports tend to reveal a very high prevalence of offending in teenage years, which makes the before-after distinction somewhat meaningless for the question of whether opiate/crack use generates extra crime.

[62] Obviously the causal argument looks a lot stronger for those whose criminality started after their drug use, and from a counterfactual point of view (as explored in the next section) these individuals will actually affect aggregate crime levels more because there is a stronger case for virtually all their offending to be additional. So the evidence from Parker & Newcombe (1987) and other studies showing that early on in the epidemic a number of these lower risk factor types seem to have been recruited into the heroin scene and that some would go on to commit just as much crime (whilst addicted) as those whose delinquency pre-dated the drug use, is crucial.

Drugs-cause-crime[63]

> ***Psychopharmacolgical***: Crime occurs when the use of drugs results in change or impairment in cognitive functioning[64].
>
> ***Economic-Compulsive***: Individuals commit acquisitive crime in order to buy drugs.
>
> ***Systemic***: Because buying and selling drugs is a lucrative, but illegal activity, offending often surrounds those who take part in it. So drugs markets can give rise to violence between dealers competing over territory, or to theft of drugs/money by potential buyers or sellers in the system.

Crime-causes-drugs

> ***Psychopharmacological***: Individuals take drugs to find the courage to commit an offence.
>
> ***Surplus proceeds of crime spent on drugs***: Some offenders report that they bought and consumed opiates and crack as rewards for committing a particularly lucrative offence. (Bennett & Holloway, 2009)

The findings revealed that almost 90% of the narratives were classified as \`drug-causes-crime', with the economic motive being by far the most important individual mechanism, accounting for 56% of the narratives (*ibid.*). Despite this, the authors found that it was often very difficult to say in which direction the causality lay, and that criminality and drug misuse often seemed to mutually reinforce each other.

Even so, their findings are generally mirrored across other self-report studies. OCUs themselves often say that they committed a high percentage of their acquisitive crime in order to buy drugs and that a far smaller percentage can be attributed to the crime-causes-drugs hypothesis (van der Zanden *et al*, 2006). To give a UK example: in the NEW-ADAM study of arrestees, 83% of offenders who said that their drug misuse and offending were linked said the connection was that they needed money to buy drugs. The psychopharmacological (drug-causes crime) explanation was the second most common reason, with 27% of those who saw a connection citing this. Just 8% said that they used the money from crime to buy drugs and hence that crime drove drug use rather than vice versa (Bennett and Holloway, 2004). The only exceptions that could be located were studies that looked at younger OCUs. Johnson *et al* (1991) using self-report data from a sample of 14-20 year-old US youths found that only 30% of the most intensive offenders said they committed crimes in order to finance drug or alcohol consumption.

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[63] These categories are taken from Goldstein, 1985. Bennett & Holloway (2009) prefer the term \`lifestyle' and argue that many of the categories can be split into both drugs-causing crime and crime-causing drugs narratives.

[64] Bennett & Holloway (2009) note that this process can also follow a crime-causes-drugs connection if individuals take drugs to find the courage to commit an offence.

The evidence from cross-sectional regression analyses is also somewhat split along youth/adult lines. In a UK context, two studies by Hammersley *et al* (1989, 1990) using cohorts of Scottish OCUs with a mean age of just 15 years, offered perhaps the strongest challenge to the causal link between heroin/crack use and crime. They found considerable rates of crime and substance use across all groups and they also found that the degree of use and the amount of crime was correlated. But regression analysis showed that: "(*non-drug) crime explained opioid use better than opioid use explained (acquisitive) crime*". Coid *et al*. (2000), who found conflicting results, pointed out that for very young cohorts it is possible that the crime-causes-drugs relationship may be stronger but that this would reverse in adulthood once regular use became cemented and crime became a necessity to finance it. However, a more recent paper, using data from English OCUs with a mean age of 32, suggests that the Hammersley *et al.* findings *are* mirrored in adult cohorts (Hayhurst *et al.*, 2012). Although median drug spend over a four-week period was £910.50 amongst the acquisitive crime offenders and £240 among non-offenders, the link between drug spend and crime was weak, but statistically significant, once other factors (like poly-drug misuse) were controlled for.[65]

Klee and Morris (1994) also question the strength of the causal relationship, taking a different approach. They found a very high level of offending amongst young heroin users, in line with other studies, but they found an almost equally high level of offending amongst an otherwise similar cohort of amphetamine users, even though amphetamines are far cheaper, which meant that this group spent much less on drugs. Like Hammersley *et al.* (1989; 1990) they concluded that the direct need to finance use did not seem to be the main explanation for offending, and hence an underlying third factor causing both crime and drug use was more important. It is worth noting that their offending measure was a binary one (whether the individual had committed crime in the last six months), and it would have been interesting to see if the results held had they looked instead at total offending. But overall, this study, which collected data almost exactly in line with the crime peak, does potentially imply that there were other mechanisms at work during the major surges in crime of the early 1990s. In particular the authors highlight peer networks as important (a conclusion echoed in Hammersley *et al*'s research). It certainly seems possible that as the number of acquisitive crimes increased, theft became `normalised' to some degree amongst groups of friends, and that the illicit nature of drug-taking (be it heroin or any other type of banned substance) encouraged this normalisation to some degree.

Arguably though, the strongest methodological approach for isolating causality comes from longitudinal studies. This is because, even if a third

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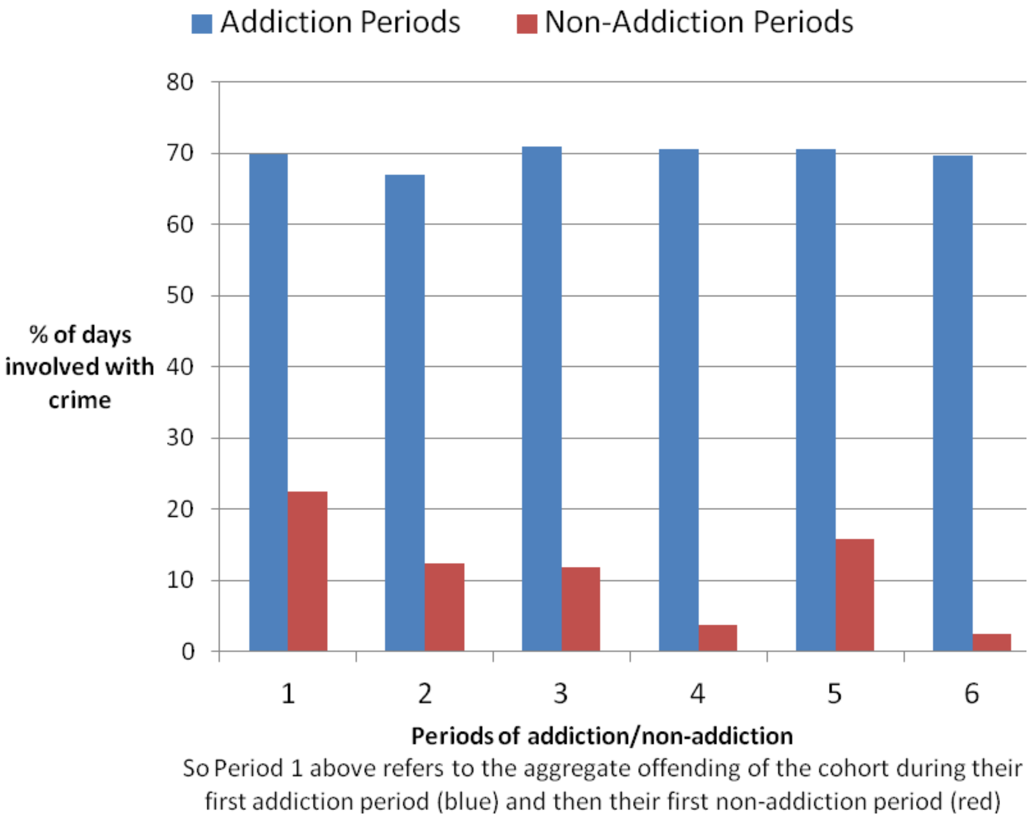
[65] Further studies of this type would need to be undertaken to see if the results can be replicated. It is possible that the Hayhurst et al study does not quite capture the required relationship. Ideally the dependent variable in a regression looking at the relationship between drug spend and acquisitive crime would be the *gap* between the individual's legal (and drug-dealing) income and their drugs expenditure. This is extremely hard to obtain given data limitations, and it is not quite clear whether this is reflected in the Hayhurst et al study.

factor (or combination of factors) does make people both more likely to commit crime *and* take opiates/crack, it is still possible for drugs to cause additional offences if the drug-taking accelerates the frequency of offending, or extends the criminal career. The evidence from the few longitudinal studies that have been undertaken suggests this is the case, though it should also be acknowledged that these are retrospective studies (see Chapter 1 for the limitations of these) and were carried out in the US.[66]

One of these, a study featuring a longitudinal cohort of heroin users by Nurco *et al* (1989) concluded that, “crime patterns established before addiction” were “intensified” by regular use of heroin, which increased the frequency of offending. This is shown even more clearly in a series of studies which followed users for a number of years. They found that heroin addicts tended to cycle in and out of addiction after first onset, and that their criminality declined dramatically when not addicted. This is crucial because if heroin use *and* criminality were caused entirely by a third factor, then there should be little difference between offending levels during periods of addiction and non-addiction, within the same individual, once age is accounted for. But a study of 354 narcotic addicts in Baltimore showed that crime rates during periods of addiction were (on average) around six times higher than during periods of non-addiction (Shaffer, Nurco, and Kinlock, 1984; Ball *et al* 1983) – see Figure 44 below.

[66] The longitudinal studies examined in the following section are limited to those that follow cohorts of opiate/crack users over time. These represent only a small subset of the vast body of research on criminal careers and it is important to acknowledge that there are studies within that literature which reach conclusions apparently at odds to those cited here. For example, some criminal career studies find a generally constant rate of offending, by individual, rather than distinct periods of acceleration or deceleration (see for example Schuster *et al*, 1978 and Tarling, 1993). There are several possible reasons for this discrepancy. The most obvious is that these studies give aggregated findings. Because the addiction cycles of drug users are not uniform (i.e. it’s not as if everyone quits for the first time at 23 and re-lapses again at 25), averaged-out findings could still give constant offending frequencies, unless they use the addiction/non-addiction periods themselves as the temporal measure. But also, criminal career studies looking at offending as a whole obviously contain many non-drug-users, hence findings may not be representative of opiate/crack users specifically. Finally, as Farrington et al (2006) point out some studies use criminal justice statistics, which can bias the results due to the restriction on the number of court referrals per offender per year. This also has the effect of dampening changes in offending frequencies.

Figure 44: Longitudinal comparison of offending during addiction and non-addiction periods



Source: chart created from data available in Ball *et al*, 1983

Anglin & Speckart (1986) took this analysis a stage further, calculating self-reported offending rates at different points throughout the drug-crime career. They found that offending rates increased by a factor of four when comparing the period before first daily use and the period immediately after, and that offending levels were six times the pre-regular-use rate in the period before first treatment.[67] They also found that as soon as users quit, their offending declined to levels very similar to those seen before first use.

Separate cross-sectional (and hence arguably less robust) European research also reached the conclusion that regular opiate/crack use accelerates offending. For example, a Swiss study found rates of property crime were around three times higher among current users of hard drugs compared with former users and non-users (Killias, 1994). These findings echoed similar results from an earlier German study (Kreuzer, 1991). Killias also looked at self-reported drug use and offending in youth cohorts from twelve European countries and found that offending rates among users of cocaine and opiates were approximately ten times greater than non-users and around three times greater than users of other drugs (Killias, 1999). UK

[67] Importantly, this does not mean that the period before treatment marked the peak in offending. The study just measured the period after first daily use and the period immediately before treatment. This makes it difficult to compare directly with the Ball et al (1983) study as the period before first treatment may not be the end of the first period of addiction. It is perfectly possible that people managed to quit for a period without treatment and then subsequently relapsed and went to treatment.

evidence is more limited, but it is consistent – see for example Parker *et al*, (1987) and Jarvis & Parker (1989), which find clear acceleration in conviction rates after heroin initiation and that the focus of individuals' criminality shifted from a variety of offence types to predominantly acquisitive offending.

There is also evidence that opiate/crack use extends criminal careers. In a study using the Buffalo Longitudinal Study of Young Men, Welte *et al*. (2005) concluded that drug use often prevents the normal maturing out of offending and means that individuals continue to offend at high frequencies into their forties and fifties. There is tentative support for this too in Figure 44 above. With the exception of period 5 (by which time sample sizes are getting low) offending decreases in the non-addiction periods over time, which would fit with the normal maturing out of crime identified by Sampson & Laub (2005) and others. But, there is no such evidence of maturing out during addiction periods.

It is also worth noting, as Coid *et al* (2000) point out, that if drug use does not cause crime there would be no logical reason for expecting drug treatment to lower criminality, yet on the whole the evidence suggests that it does (see, for example, Killias and Ribeaud, 1999; Killias *et al*, 2000; Bukten *et al*, 2013).[68]

To summarise then, although the evidence is consistent in many areas, particularly the magnitude of OCU offending and the fact that it is skewed towards a small number of offenders, it is conflicted in relation to causality. As many OCUs do not become persistent offenders and many start offending before taking opiates/crack, several authors suggest that there is a third factor that drives both offending and opiate/crack use. This is further reinforced by studies like Macleod *et al* (2013) and Conroy *et al* (2009), which show that certain factors relating to childhood adversity (for example having violent or criminal parents) predict both offending *and* a propensity for drug use.

A key conclusion from this paper though, is that even if a third factor is important, this may not preclude a role for the heroin epidemic in driving crime trends. To see this – consider the following thought experiment. Imagine a hypothetical third factor that causes an adult offending rate of five in the absence of a heroin epidemic, but *also* a susceptibility to heroin, which leads to an adult offending rate of 10 if an epidemic occurs. In that scenario – the third factor clearly `causes' five crimes, as these occur whether the epidemic happens or not. But five crimes are driven by the *interaction* between the third factor and the presence of an epidemic. Or, to put it another way, in the absence of the epidemic there would be five fewer crimes, but preventing the individual from suffering the third factor would also prevent those five crimes (and another five into the bargain). This analysis is highly simplified, but may

[68] In this context (and recalling the example of Merseyside), the fact that methadone prescriptions increased at their fastest rate between 1992 and 1995 (both in absolute and proportional terms) has important implications for the subsequent decline in crime, particularly in helping to explain why crime might have started falling before the total number of users peaked. (See http://www.ncbi.nlm.nih.gov/pmc/articles/PMC169636/)

help to make sense of some of the apparently conflicting evidence presented above.[69]

In this context it may also be important that recent cohorts of young people seem to be less vulnerable to drugs epidemics, and indeed more resilient to risky behaviours of all kinds: drinking, smoking and drug use have all declined in UK youth populations in recent years. This would fit with an underlying shift in propensity for crime *and* drug use.

Aside from the need to research this possibility further, two tentative conclusions emerge.

- Regardless of the causality question, the large change in the number of OCUs over the last 35 years and the strong evidence of their high *aggregate* rate of offending means that the cohort itself is likely to have played a role in the rise and fall of crime, even if most of the offending was ultimately driven by a third factor.

- Opiate/crack use *is* likely to be causally related to crime to a degree, though the magnitude remains uncertain. For the group who start offending in line with or after initiation into regular opiate/crack use, this seems clear, but even for those whose offending preceded drug misuse, studies suggest that opiate/crack use would be likely to have accelerated their rate of offending and extended their criminal career to some extent,[70] which would cause additional offending in the aggregate.

Parker (2004) sums up this evidence well:

"*Heroin use produced an extension and amplification of a deviant lifestyle rather than created it."* (Parker, 2004).[71]

If the above observations are correct (and this paper accepts that there is certainly some conflicting evidence) then some correlation between opiate/crack use and acquisitive crime should be evident at the local/national and international level. This is examined in the next chapter.

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[69] For example, Chaiken & Chaiken (1990) review the longitudinal evidence and conclude both that there is clear evidence of acceleration in offending driven by drug use but also that third factor causality is the most important mechanism.
[70] Even Hammersley et al (1990) write that: "(though) our findings refute the legend that heroin regularly compels otherwise honest people to become criminals.... once the habits of drug use and crime are established, each may worsen the other."
[71] Though as noted, we would simply add that whilst this is true for the majority of OCUs that offend, for an important minority it seems as though heroin use *did* create the onset of offending.

Chapter 5: The relationship between opiate/crack use and crime locally, nationally and internationally

The previous Chapter presented a summary of existing evidence for and against the existence of a causal link between heroin/crack use and crime. This section attempts to add to that evidence by looking at the correlation between opiate/crack use and crime over different time periods and geographies.

It is important to emphasise again that the analysis presented here is intended to stimulate debate and further examination of these topics and is not intended it to be definitive or seen as such. Indeed, the analysis in this section varies in the robustness both of the techniques employed and the data used.[72]

To start with, some qualitative similarities are drawn out between the crime trends from Chapter 2 and the historical overview of the epidemic outlined in Chapter 3:

Qualitative conclusions

Chapter 2 showed that recorded crime in England and Wales increased through the 1980s with a slight `lull' around 1987/88, which is particularly marked for drug-related acquisitive crimes like burglary (see Figure 6). The available indicators of opiate/crack use, despite all their weaknesses, also suggest a two-wave pattern, as does the ethnographic description of the epidemic provided by Parker *et al* (2000). Clearly, this correlation does not necessarily imply causality especially given that economic variables also show a two-wave trend at this time (Figure 20 shows this for unemployment). This is explored further in the statistical testing that follows.

Chapter 2 showed that overall crime peaked in the early-to-mid 1990s, as did the number of new OCUs, according to evidence from Chapter 3. Almost all police force areas were affected by the second wave of the epidemic, which occurred in line with the crime peak, whereas only a handful were markedly affected by the first wave. In addition, the second wave seems to have involved more established and more male users with an emphasis on injecting heroin rather than smoking it (Strang & Taylor, 1997). These factors might also have resulted in a greater crime impact.

Turning to the crime peak, the review of local data demonstrated that many police force areas experienced a sharp `spike' in multiple acquisitive crime-types, and that it was hard to explain these spikes via other theories of crime causation. An important question then is to what extent the evidence on opiate/crack use suggests that the epidemic would have caused a sharp increase and then decrease in crime in each area. Certainly, it is clear from available data that once an epidemic takes hold, the number of new users

[72] Our tentative feeling is that these two dimensions of robustness somewhat offset each other. That is, as the techniques get more sophisticated they place a heavier weight on the robustness of the data, which is means they are not necessarily more reliable, but we welcome others' views.

also tends to spike. It is not clear though, that the number of total users also follows this pattern. Some models, notably those outlined in Rossi (2002) suggest that a graph over time of total users would also show a degree of `spike.' But ultimately this depends on resolving the debate around cessation rates outlined in Chapter 3. If it is true, as studies like Heyman (2013) suggest, that cessation rates are roughly constant from initiation onwards then prevalence will not spike, but will decline more slowly than incidence. But if instead it is the case that cessation rates in the first couple of years are actually far higher, as suggested by Sweeting *et al* (2009) and Kaya *et al* (2004) then prevalence will also display a spike to some degree.[73]

But there are other factors to bear in mind too given that any link between opiate/crack use and crime would be a function of both the number of users *and* their offending rate. If the offending rate decreased significantly once the incidence peak was reached, then crime would also tend to fall away quickly. In relation to this, we have seen strong evidence from longitudinal studies like Ball *et al* (2003) that, during the early phase of an opiate/crack career, the offending rate (for the cohort in aggregate) is high, but not markedly higher than during subsequent periods of addiction (see also the DDW analysis in Chapter 6). Thus, there is no strong evidence at all to suggest a marked decrease in the offending rate *during periods of addiction.* However, the offending rate for the cohort as a whole might show a different pattern. To see this, consider the full set of data from the Ball *et al* (1983) study, which is reproduced in Table 6 below.

Table 6: Length of addiction and non-addiction periods in a US study

ADDICTION PERIODS				
Period	Average length (days)	Number of users	% of days in crime	Total crime days
1	815	354	69.8	201,380
2	583	297	66.6	115,319
3	470	226	70.9	75,310
4	441	153	70.5	47,568
5	453	100	70.5	31,937
6	342	57	69.7	13,587
7	393	38	92.2	13,769
8	315	22	64.7	4,484
9	360	13	69.8	3,267
10	368	8	100	2,944
Total	4540			
Years	12.44			

[73] There is an argument that those who use opiate/crack for only a year or two are not particularly relevant to crime figures because their usage is unlikely to last long enough for them to be financially dependent and hence involved in acquisitive crime. Evidence that this is probably not justified, is presented in Chapter 6.

NON-ADDICTION PERIODS				
Period	Average length (days)	Number of users	% of days in crime	Total crime days
1	887	319	22.4	63,381
2	754	167	12.4	15,614
3	625	78	11.9	5,801
4	533	32	3.7	631
5	639	14	15.8	1,413
6	690	6	2.5	104
7	750	2	0	0
8	510	1	0	0
Total	5388			
Years	14.76			

Source: Ball *et al*, 1983

Although the rate of offending *per individual* is consistent throughout addiction periods, the total *volume* of offending is highest in the first period of addiction and declines rapidly thereafter. This is partly because some users quit completely between addiction periods, hence the overall size of the group gets whittled down, but it is also due to a reduction in the length of addiction periods. The second table shows that offending is significantly reduced during periods of non-addiction, but it also shows that as the drug-using career of the cohort progressed, the number of days in non-addiction grew relative to days in addiction. This is crucial because at the incidence peak, there will have been a high proportion of users in the early stages of their opiate/crack use career – i.e. in the first period of addiction. Moving forward from the peak year by year, a greater and greater proportion of the cohort would be in a period of non-addiction and have a far lower offending rate.

There is one final reason why crime trends might have declined sharply after the incidence peak, though it is complex and might be thought of as a `counterfactual effect’. As outlined in Chapter 4, Parker & Newcombe’s (1987) analysis tentatively suggested that OCUs can be divided between those who were regular offenders before taking heroin (many of whom had multiple other crime risk factors) and those who were not offenders first and who tended to have fewer risk factors. But the analysis also suggested that during addiction periods these two groups could end up committing very similar levels of crime. From a counterfactual perspective however, the impact of the second group would actually be bigger, because in the absence of the epidemic they would probably have committed far less crime than the group with multiple risk factors. This has implications for the post-incidence peak because evidence also shows that it is this second group who are generally able to quit opiate/crack use faster, especially if greater employment opportunities are available (Kaye *et al*, 1998).[74] In other words, it seems likely that many of this group, who were pushing up crime significantly at, or just before the incidence peak, would have exited the population before the prevalence peak, causing a potentially faster rate of crime decline at this point.

For these reasons it seems at least possible that crime might have declined quite quickly once the incidence peak was reached. Clearly though, this is an area that requires further examination, particularly in a UK context, as these conclusions rely heavily on the findings from a few US longitudinal studies.[75]

Fortunately, the evidential relationship is somewhat simpler when it comes to looking at why all types of theft tended to rise and fall together throughout the different police force areas in England and Wales. This would clearly fit with several of the potential drugs-cause-crime links explored in Chapter 4. Most obviously, if regular drug use creates an income gap that cannot be filled by legitimate income then we might expect an increase in all types of theft-related crimes to occur simultaneously.[76]

The epidemic narrative also offers a potential explanation for some of the local variation we saw in crime trends. London, the only area to have a pre-existing cohort of users, was less affected, in relative terms, than other large, urban police force areas. The clearest example though is Merseyside's earlier crime peak, which fits closely with the evidence on epidemic spread. Merseyside was one of the first areas to be affected, but also, seemingly, one of the first areas to be free of the epidemic, perhaps due to its faster adoption of treatment services. It is also clear that, beyond Merseyside, other areas were affected by the epidemic to different degrees at different times so if opiate/crack use and crime are causally linked, their crime peaks would be likely to vary also. This is tested more formally later in this Chapter.

The story of the epidemic may also offer clues as to why the crime peaks were more pronounced in the less urban police force areas. Most of the

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[74] Which of course they were – recall the unemployment trend from Figure 20 which shows massive falls in unemployment from 1993.

[75] The Anglin & Speckart (1986) analysis also suggests that offending frequency increases significantly during the first period of addiction compared to the period immediately previous. However it also hints at a possible escalation in offending frequency through to period of first treatment, which might be taken as evidence that crime levels would persist or even increase post incidence peak. This is possible – but it is also possible that crime escalated *within* the first period of addiction, as Anglin & Speckart only measure the immediate period post-initiation. In either case, it of course remains true that the closer to the incidence peak the higher the percentage of the sample that will be in the first phase of addiction and not in a treatment or non-addiction phase.

[76] The one exception to this might be the component of `theft of vehicles' that is actually joy-riding and hence not for economic gain. In 1980 this probably made up a large part of the total volume of theft of vehicles as around 80% of vehicles were recovered (which probably indicate joy-rising though there are other possibilities like using a stolen vehicle to commit another crime and then dumping it). But during the 1980s this percentage declined significantly so that by the 1990s around 60% of thefts were recovered, hence a greater proportion probably were for economic gain. This trend is matched by a comparison of theft of and from vehicles, which shows that through the 1980s the rate of theft of vehicles (by number of cars on the road) was almost flat whereas the rate of theft from vehicle increased significantly. Overall then it would seem like the economic motive for vehicle crime increased markedly through the 1980s and early 1990s while the thrill-seeking component was flat or even declined.

metropolitan forces were affected by both epidemic waves, or more likely, had a series of epidemics in separate urban localities, some in the 1980s and some in the 1990s. This could be why their crime rises are more spread temporally. But many of the non-Metropolitan forces have just one urban centre, and these tended to be affected in the second wave of the epidemic, which may be why they had such pronounced spikes in crime at this time.

Post-peak, there are other facts to consider, particularly the tentative signs of ageing within the offender population and the possibility of a cohort effect. The analysis of the OCU population showed a very similar pattern though it is also true that there are other possible explanations for an ageing offender population, like more youth diversion within the criminal justice system.

Also, there is the fact that the crime decline was driven by a fall in repeat victimisation. There is no hard evidence to suggest a link between repeat victimisation and opiate/crack use. However, there is a certain logic to the proposition, given the evidence both that theft offenders tend to commit their crimes close to home (Wiles and Costello, 2000) and that a small number of offenders commit the vast majority of offences. One heroin user (quoted in Parker *et al*, 1988) aptly sums up how the rise and fall of an epidemic might have had a large effect on trends in repeat victimisation:

"*I started going out burgling. I'd never done anything like that before. It wouldn't have entered my head but when I was strung out I'd have done almost anything. I'd just walk down the road to all them shops and knock one of them off. Bring the stuff back; stash it till morning and then sell it to buy some gear. I did that about 30 or 40 times going through each individual shop in a row. I only ever burgled shops. I did go out once with a mate to a house and I just looked at all these photos of, y'know like, kids and stuff, and I just got out the window and walked away. I didn't pick up anything*."

Source: Parker *et al*, 1988

Finally, if opiate/crack use was a more important driver of both the rise and fall in crime during the 1990s/2000s than economic variables, then the continuing crime decline through the recession is less surprising that it appears, because there is evidence that the size of the OCU cohort has continued to fall at the same rate despite the downturn (Hay *et al*, 2012). [77]

The relationship between the Addicts Index numbers and crime by police force area in England and Wales

Preliminary analysis

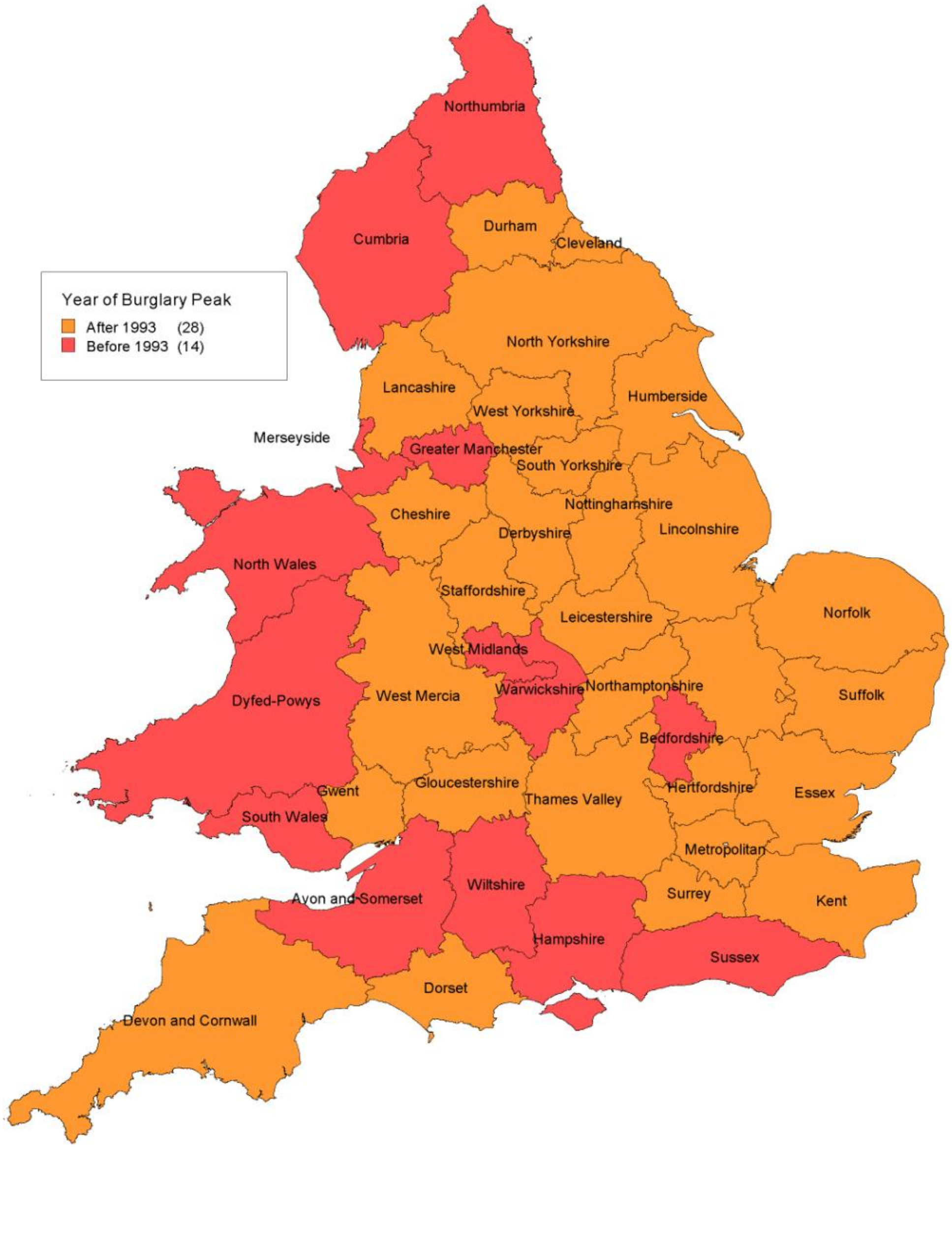
To analyse more robustly some of the links suggested above, data were gathered on new and total heroin users (from the Addicts Index), unemployment (from NOMIS) and recorded crime (from the Home Office

[77] In addition, 77% of the DTORS sample (a study conducted just before the recession hit) were already unemployed, so the rise in joblessness generated by the downturn would have been unlikely to affect this group markedly.

recorded crime archives) for the period 1980 to 1997.[78] The data were all collected at police force area level. A series of tests were then conducted, with increasing levels of sophistication.

Firstly, police force areas were divided into two groups, those with a burglary peak before 1993 and those with a peak after 1993. The results were mapped, see Figure 45 below. The idea was to see whether the areas that were affected earlier in the epidemic also had earlier crime peaks. Generally, western areas have earlier epidemics than Eastern areas and it is clear that the peaks in burglary also follow this pattern to a reasonable extent:

Figure 45: Burglary peaks pre- and post-1993 by police force area

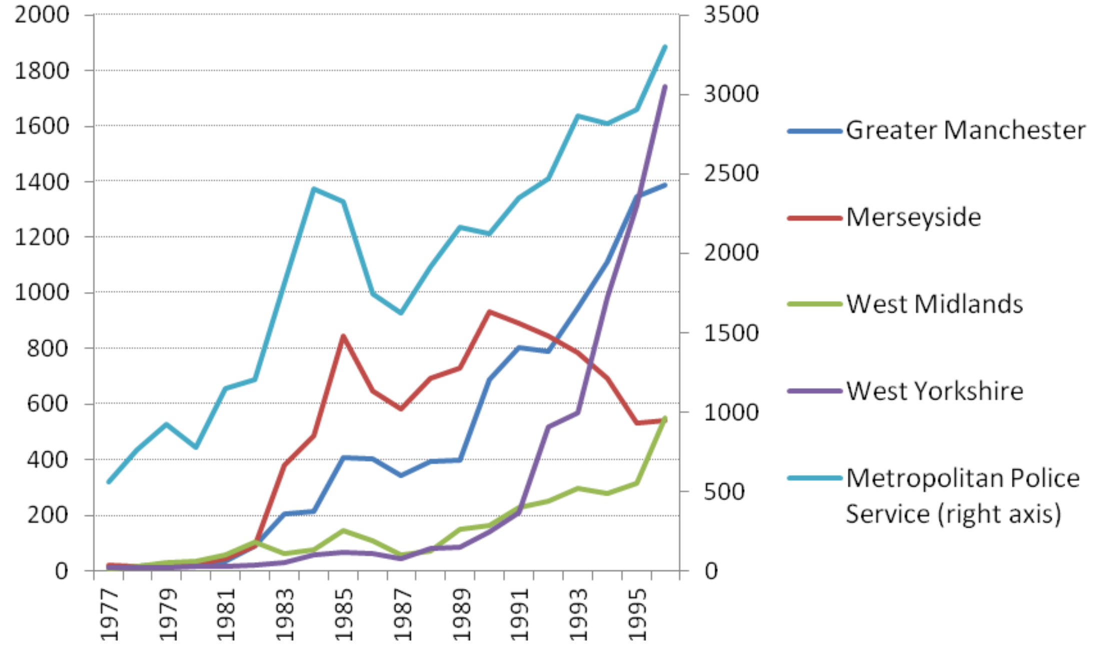


[78] There are several reasons for stopping at 1997. Most importantly, the Addicts Index data were discontinued at this point, but recorded crime data also became less consistent between 1998 and 2004 due to recording practice changes.

Next, the trends in new heroin users for the five police force areas with the highest burglary volumes in 1980 (Figure 37 above, reproduced below) were compared to the trends in recorded burglary for these areas (Figure 46):

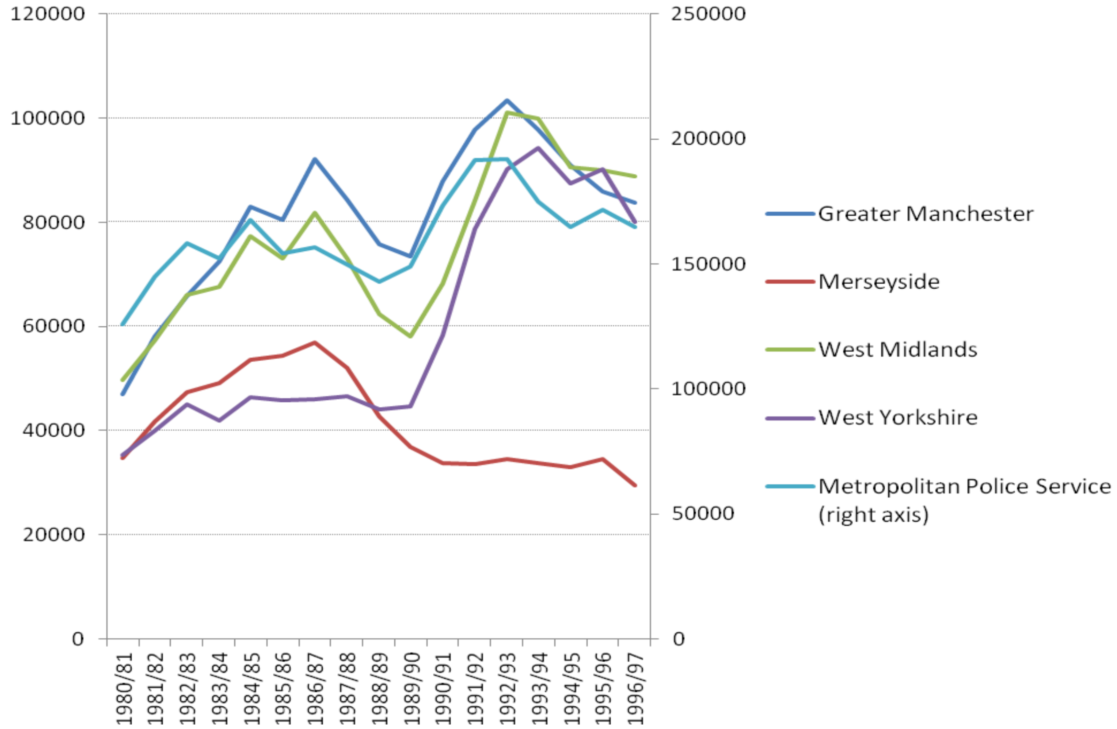
Figure 46: A comparison between trends in new heroin users and trends in recorded burglary in five police force areas, 1977 to 1995

Numbers of new heroin users



Source: Addicts Index

Recorded burglary volumes



Source: ONS police recorded crime.

Figure 46 shows that Merseyside, having seen a marked increase in new users notified to the Addicts Index in the mid-1980s, had a declining trend by the 1990s. Of these areas, it is the only one that might be considered to have been affected by the first epidemic wave only. London and Manchester were clearly affected by both waves, while West Yorkshire (and to a lesser extent West Midlands) were only affected by the second wave.

Figure 46 also shows that this pattern is generally mirrored in the crime data. Merseyside had a large burglary rise in the 1980s but nothing in the 1990s. Areas affected by both waves (London and Manchester) saw rises in both phases, and areas affected only by the second wave (West Yorkshire) had only moderate growth in crime in the 1980s, but then had a huge increase in the 1990s. Arguably the one area that does not quite fit the pattern is the West Midlands, which had a lower level of new users throughout, yet had quite marked increases in burglary in both waves.

Apart from the correlation between new heroin users and crime, the charts are also noteworthy for their indication of the lag on the drugs data. Merseyside's crime is already declining by 1987 (in line with Parker's description of the incidence peak), *four years before* the number of new heroin users peaked on the Addicts Index. If this pattern were to be mirrored nationally, a 1993 crime peak (for recorded acquisitive crime) would not be reflected on the Addicts Index until 1997, after the series was discontinued.

Correlation coefficients

We restrict the charts above to just the highest-crime-volume police force areas for ease of presentation, but the next set of analyses use data from all 42 police forces.[79] A series of correlation coefficients were calculated for the period 1983 to 1996. For the opiate/crack use variables, new heroin users and total addicts notified were used. And for the crime variables, burglary, theft of vehicle and theft from vehicle were tested. Also, given the high degree of correlation at the national level (see Figure 20), coefficients for the correlation between unemployment and these crime types were also produced.

In each case, four variations were tried to see if relationships were robust.

- In the first variation police forces were ranked for every year, by their levels of crime, OCUs and unemployment. A Pearson correlation coefficient was then calculated based on these ranks, across all years and for all forces.

- The second variation used *volumes* of crimes/OCUs/unemployed rather than ranks.

[79] The City of London was excluded due to its small size, and British Transport police was also left out. Not being a geographical force, it does not have an OCU population as such.

- The third variation also used volumes but excluded the Metropolitan Police Service as it generally had markedly higher levels for all three variables, which may skew the correlation.

- Finally, for the same reason, a fourth variation that excluded several more outliers was performed.[80] The results are shown in Table 7.

Table 7: Correlation coefficients between acquisitive crimes and opiate/crack users and unemployment across all police forces[81], 1983 to 1996

		Correlation coefficients		
		All addicts notified	New heroin users	Un-employment
Burglary	Ranks	0.69***	0.61***	0.14**
	volumes (all)	0.79***	0.84***	0.92***
	volumes (exc. London)	0.54***	0.61***	0.85***
	volumes (exc. other outliers)	0.49***	0.47***	0.85***
Theft of vehicle	Ranks	0.66***	-0.10*	0.02
	volumes (all)	0.74***	0.81***	0.88***
	volumes (exc. London)	0.55***	0.58***	0.77***
	volumes (exc. other outliers)	0.44***	0.41***	0.75***
Theft from vehicle	Ranks	0.72***	0.63***	0.11**
	volumes (all)	0.80***	0.84***	0.90***
	volumes (exc. London)	0.55***	0.61***	0.81***
	volumes (exc. other outliers)	0.51***	0.49***	0.81***

Note: *** = statistically significant at 0.1% level.
** = statistically significant at 1% level.
* = statistically significant at 5% level.

Sources: Addicts Index; police recorded crime; NOMIS

Table 7 suggests that there is a potentially strong relationship between both the OCU variables and acquisitive crime and between unemployment and acquisitive crime. However, whereas the OCU variables were robust to all specifications (with the exception of the rank correlation between new heroin users and theft of vehicle), the unemployment correlation, which was large for the volume-based variants, almost disappeared when using rank correlation.

A problem with the above analysis is that it takes no account of the probable `lag' on the Addicts Index data. Regular users tended not to be notified to the index immediately and the length of time taken would be likely to vary by individual. Hence, it is not the case – even if heroin/crack use was the most important causal variable – that there would be exact correlation between

[80] These were all areas with a total increase in heroin users greater than 1500.
[81] Excluding City of London and British Transport Police.

crime in a given year, and the Addicts Index variables, *in the same year,* which is effectively what the above analysis is testing.

To try and mitigate this, an alternative formulation looking at the total *increases* in crime and OCUs (or unemployment), from 1983/84 to peak in each case was tested. The peak year for each variable will be different across areas, so the time periods of the correlation do not match. Essentially, the analysis asks the question: did the areas that had the biggest rises in OCUs also have the biggest rises in crime, regardless of when exactly those rises began, and when they peaked. This was tested using the same four variants as previously. The results are shown in Table 8 below:

Table 8: Correlation coefficients between increases in crime and increases in total addicts/new heroin users/unemployment

		Correlation coefficients		
		All addicts notified	New heroin users	Un-employment
Burglary	Ranks	0.69***	0.74***	0.33*
	volumes (all)	0.66***	0.82***	0.43**
	volumes (exc London)	0.63***	0.79***	0.28
	volumes (exc other outliers)	0.76***	0.82***	0.44**
Theft of vehicle	Ranks	0.55***	0.65***	0.06
	volumes (all)	0.42**	0.70***	-0.03
	volumes (exc London)	0.68***	0.78***	0.08
	volumes (exc other outliers)	0.55***	0.69***	0.19
Theft from vehicle	Ranks	0.72***	0.73***	0.36*
	volumes (all)	0.85***	0.75***	0.72***
	volumes (exc London)	0.69***	0.76***	0.29
	volumes (exc other outliers)	0.60***	0.59***	0.46**

Note: *** = significant at 0.1% level
** = significant at 1% level
* = significant at 5% level

Sources: Addicts Index; police recorded crime; NOMIS

The table shows large and strongly significant correlation between increases in the OCU variables and increases in crime. The relationship between increases in unemployment and increases in crime is smaller and weaker – it is only significant in certain specifications and for certain crime types. The comparison can be seen more graphically on the scatter-plots below, which use burglary as an example.

Figure 47: Correlation between increases in the number of burglaries and increases in the number of OCUs, by police force area[82]

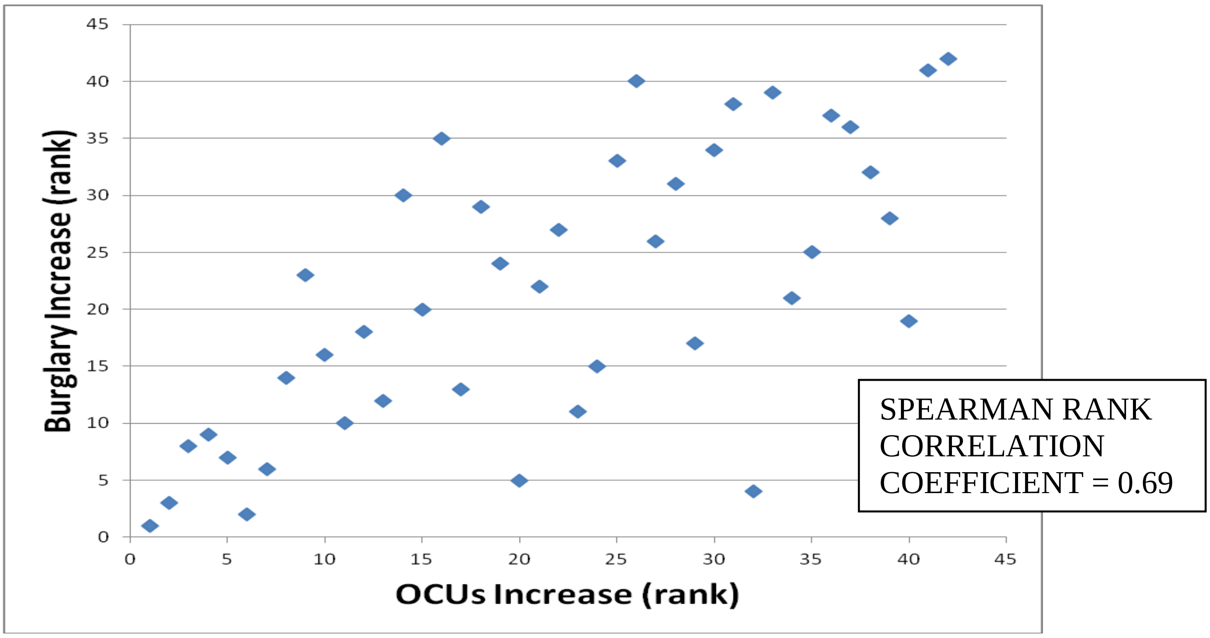
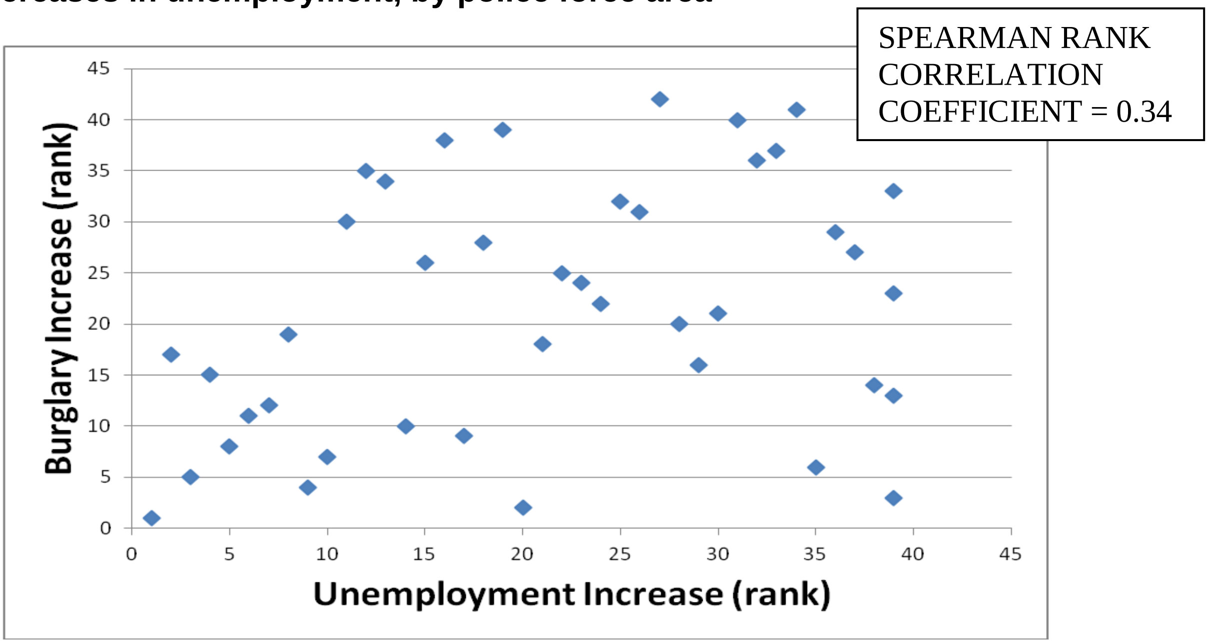


Figure 48: Correlation between increases in the number of burglaries and increases in unemployment, by police force area



Each of the dots in these charts represents a police force area. It is clear that those areas that had the biggest increase in burglaries also had the biggest increase in opiate/crack users, but *not* necessarily the biggest increases in unemployment. In fact, the unemployment correlation disappears completely if volumes are used rather than ranks and if London is excluded, whereas the

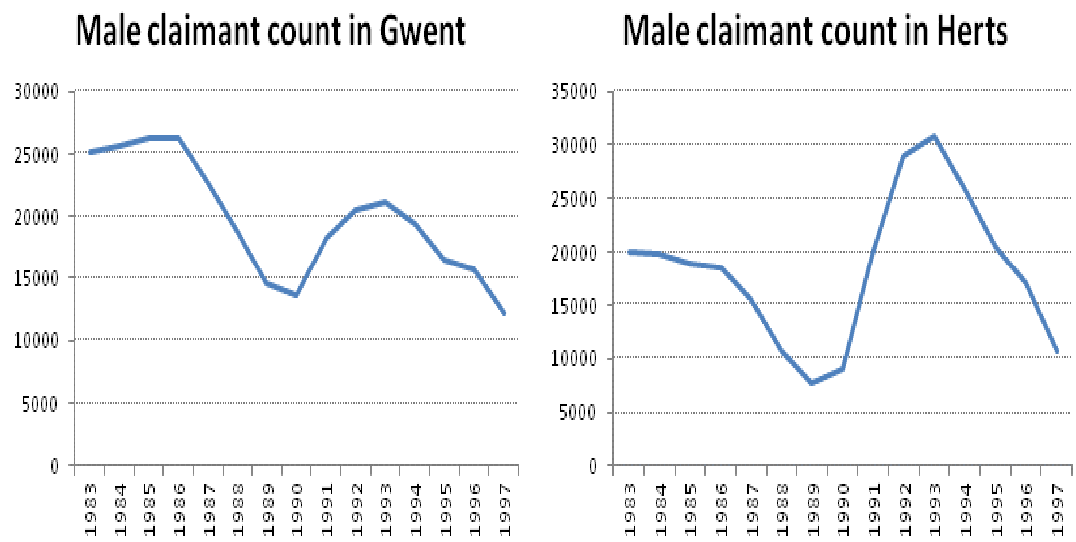
[82] Note that the one outlier on this chart – the blue dot on the bottom right with a big rise in OCUs but a small rise in burglary is Merseyside, which, as detailed elsewhere, has an epidemic-related explanation.

drug correlation stays robust to these changes and explains 40% of the variation in crime increases between forces.[83]

The relationship between heroin use and unemployment

Inspecting the data further and particularly the separate force-level charts for crime, unemployment and numbers of OCUs, revealed that looking for separate relationships between unemployment and crime, and between OCUs and crime may be a mistake. It seemed from the charts that there may be an interaction between drug use and unemployment that drove particularly high crime levels.[84] To try and test this, unemployment trends by area were examined. This showed that of the 42 police force areas, 20 were like Gwent in Figure 49 below, and had higher unemployment peaks in the 1980s. The other 22 were like Hertfordshire, and had a higher peak in the 1990s.

Figure 49: Examples of the variability in unemployment trends, by police force area, 1983/84 to 1997/98



Source: NOMIS

The forces were separated into these two groups: those with early unemployment peaks and those with late unemployment peaks.

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[83] Note that we excluded London from the analysis with volumes to avoid the creation of spurious correlation, which can occur when one area has a far higher volume than all others.

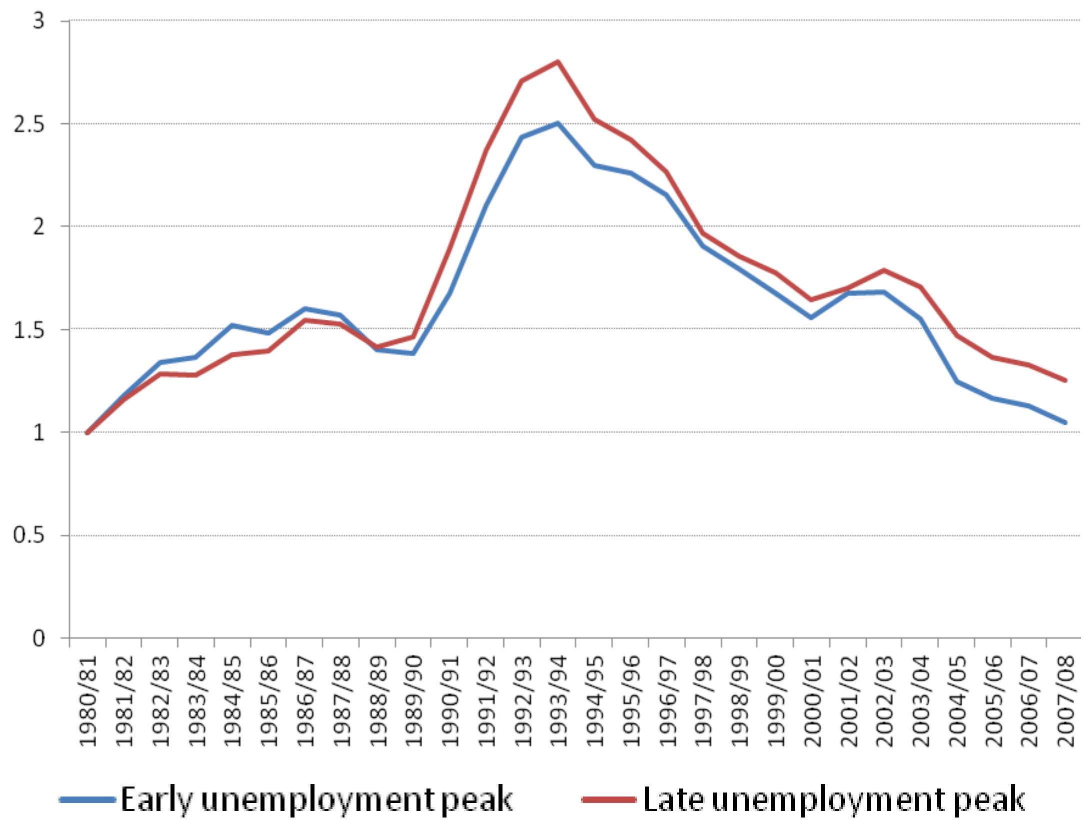
[84] A literature review revealed that many studies have investigated the relationship between substance use and business cycle fluctuations in unemployment (see Henkel, 2011 for a review) with the general conclusion that whilst smoking and drinking are mildly pro-cyclical, illicit drug use is counter-cyclical. i.e. it increases during recessions and subsides during booms, which would fit the hypothesis presented here. However, only one paper could be located that specifically analysed the crime effect of a possible interaction between unemployment and illicit drug use: Baumer et al, 2012. This paper concluded that there was no interaction effect on property crime, but its measure of drug use was very different to that employed here. It looked at police arrests, rather than drug use variables, because the focus was on seeing whether there was a relationship between crime, economic cycles and growth in drug *markets* (for all types of illegal drugs), rather than on the more specific hypothesis tested here – that unemployment interacts with heroin/crack *use* to drive up crime.

Table 9: Police force areas divided between those that had an early unemployment peak and those that had a later peak

Unemployment Peak	
1980s	1990s
Cheshire	Avon and Somerset
Cleveland	Bedfordshire
Derbyshire	Cambridgeshire
Durham	Cumbria
Dyfed-Powys	Devon and Cornwall
Greater Manchester	Dorset
Gwent	Essex
Lancashire	Gloucestershire
Lincolnshire	Hampshire
Merseyside	Hertfordshire
North Wales	Humberside
North Yorkshire	Kent
Northumbria	Leicestershire
South Wales	Metropolitan
South Yorkshire	Norfolk
Staffordshire	Northamptonshire
Warwickshire	Nottinghamshire
West Mercia	Suffolk
West Midlands	Surrey
West Yorkshire	Sussex
	Thames Valley
	Wiltshire

Aggregate burglary trends were then calculated for these two groups, indexed to 1980/81. This is shown in figure 50 below.

Figure 50: Aggregate burglary trends for police force areas that had an early unemployment peak compared to those that had a later peak



Source: NOMIS

The chart shows that areas which had earlier peaks in unemployment had very slightly higher levels of burglary in the mid 1980s and that this situation reversed during the mid 1990s crime peak. But overall it is clear that unemployment is unlikely to be the most important factor driving burglary trends given that even areas that had higher levels of unemployment in the 1980s had a collectively higher level of crime in the early 1990s. One point to bear in mind in relation to this chart (and indeed all the analysis in this particular section) is that by indexing all the areas before aggregating, we effectively weight each area equally. So, in contrast to the correlation coefficient and panel analysis (see next section), areas with high volumes of crime are weighted the same as areas with low volumes.

The areas were then sub-divided again by whether they were more affected by the epidemic in the first wave, up to around 1985/86, or the second. To determine this, the total heroin users series on the Addicts Index was used. For each area the absolute increase in heroin users notified between 1977 and 1987 was recorded, as well as the increase between 1988 and 1996.[85]

[85] Note that this also avoided the problem of the break in the series post-1987 because we never used values that spanned the break. The two periods were considered separately. Also, we took the increase

These were used as a proxy for how areas were affected by each wave. This needed to be corrected for the size of the area, so ONS population figures were used to create a rate per 10,000 resident population. This produced, effectively, an increase in each epidemic wave per 10,000 population.

It became clear that the vast majority of areas were more affected by the second wave of the epidemic. Only Merseyside can really be said to have been conclusively more affected by the first wave.[86] So to give two meaningful groups for analysis, areas were coded to the first wave if the difference between the increase in the second wave (per 10,000 population) and the increase in the first wave (per 10,000 population) was less than one. In other words, those areas that saw only a marginally greater increase in the second wave were coded to the first-wave to give two comparably sized groups for analysis. This is important to bear in mind when interpreting the results below. In addition, Merseyside was split out into a category on its own.

This entire process can be followed through using Table 10 below:

Table 10: Allocating force areas to epidemic `waves'

	Increase in notified heroin users 1977-88	Increase in notified heroin users 1977-88 (per 10,000 population)	Increase in notified heroin users 1988-96	Increase in notified heroin users 1988-96 (per 10,000 population)	Difference between increase (per 10,000 population) in first wave and increase (per 10,000 population) in second wave	Code (1=1st wave; 2=2nd wave)
Avon and Somerset	93	0.67	1240	8.92	8.26	2
Bedfordshire	35	0.68	12	0.23	-0.45	1
Cambridgeshire	2	0.03	145	2.35	2.32	2
Cheshire	150	1.59	412	4.37	2.78	2
Cleveland	4	0.07	348	6.20	6.13	2
Cumbria	49	1.02	-1	-0.02	-1.04	1
Derbyshire	19	0.21	123	1.35	1.14	2
Devon and Cornwall	61	0.43	421	2.94	2.51	2
Dorset	33	0.53	146	2.33	1.80	2
Durham	13	0.22	100	1.67	1.45	2
Dyfed-Powys	13	0.29	20	0.45	0.16	1
Essex	128	0.85	161	1.07	0.22	1
Gloucestershire	14	0.27	229	4.47	4.20	2
Greater Manchester	505	1.97	2259	8.82	6.85	2
Gwent	11	0.20	20	0.37	0.17	1
Hampshire	49	0.30	160	0.97	0.67	1

for the second wave right up to 1996 because of the lag on the Addicts Index data. As the panel data analysis shows, this probably gives us a good idea of the crime-relevant increase up to 1993.

[86] Even Cumbria and Bedfordshire, which are the only forces apart from Merseyside to have larger increases in the second wave according to the table, still had higher *levels* of users in the early 1990s than in the 1980s. Only Merseyside had a falling trend in users by the 1990s.

Hertfordshire	30	0.30	32	0.32	0.02	1
Humberside	58	0.68	701	8.21	7.53	2
Kent	102	0.68	228	1.52	0.84	1
Lancashire	225	1.63	1263	9.14	7.51	2
Leicestershire	-6	-0.07	189	2.18	2.25	2
Lincolnshire	19	0.34	83	1.49	1.15	2
Merseyside	825	5.58	23	0.16	-5.42	1
Metropolitan	1916	2.83	2098	3.10	0.27	1
Norfolk	91	1.27	249	3.46	2.20	2
North Wales	55	0.88	236	3.76	2.88	2
North Yorkshire	13	0.19	87	1.26	1.07	2
Northamptonshire	17	0.31	142	2.60	2.29	2
Northumbria	37	0.26	292	2.03	1.77	2
Nottinghamshire	18	0.18	359	3.58	3.40	2
South Wales	23	0.19	110	0.93	0.73	1
South Yorkshire	25	0.19	635	4.88	4.69	2
Staffordshire	33	0.32	654	6.42	6.10	2
Suffolk	32	0.51	148	2.37	1.86	2
Surrey	62	0.61	200	1.97	1.36	2
Sussex	90	0.66	473	3.45	2.80	2
Thames Valley	52	0.28	422	2.24	1.97	2
Warwickshire	1	0.02	52	1.08	1.06	2
West Mercia	34	0.33	236	2.28	1.95	2
West Midlands	85	0.32	555	2.10	1.77	2
West Yorkshire	56	0.27	2791	13.64	13.37	2
Wiltshire	76	1.40	112	2.06	0.66	1

Source: Addicts Index

The two groupings were then merged to produce five categories:

1) ***Early Heroin, Early Unemployment***: those areas coded to the first wave of the epidemic which had 1980s unemployment peaks.
2) ***Early Heroin, Late Unemployment***: those areas coded to the first wave of the epidemic that had 1990s unemployment peaks.
3) ***Late Heroin, Early Unemployment***: those areas coded to the second wave of the epidemic that had 1980s unemployment peaks.
4) ***Late Heroin, Late Unemployment***: those areas coded to the second wave of the epidemic that had 1990s unemployment peaks.
5) ***Merseyside*****:** which, as discussed was the only area to be completely affected only by the first wave of the epidemic (and also had an early unemployment peak).

The breakdown of these groups (other than Merseyside) is shown below.

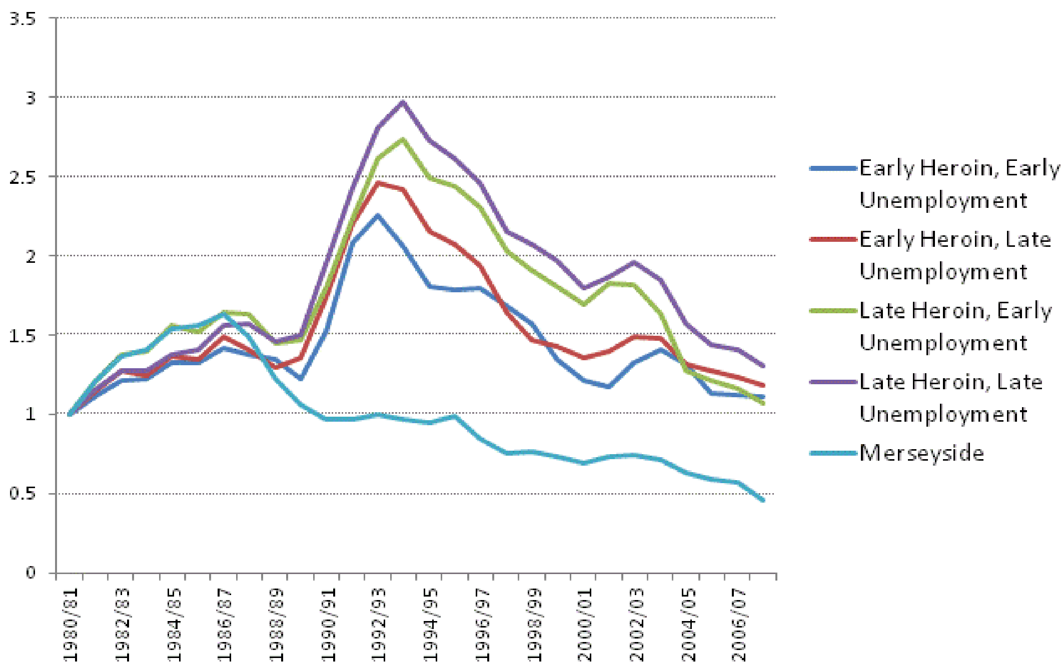
Table 11: Police force areas divided by unemployment peak and timing of heroin epidemic

Early Heroin, Early Unemployment	Early Heroin, Late Unemployment	Late Heroin, Early Unemployment	Late Heroin, Late Unemployment
Dyfed-Powys	Bedfordshire	Cheshire	Avon and Somerset
Gwent	Cumbria	Cleveland	Cambridgeshire
South Wales	Essex	Derbyshire	Devon and Cornwall
	Hampshire	Durham	Dorset
	Hertfordshire	Greater Manchester	Gloucestershire
	Kent	Lancashire	Humberside
	Metropolitan	Lincolnshire	Leicestershire
	Wiltshire	North Wales	Norfolk
		North Yorkshire	Northamptonshire
		Northumbria	Nottinghamshire
		South Yorkshire	Suffolk
		Staffordshire	Surrey
		Warwickshire	Sussex
		West Mercia	Thames Valley
		West Midlands	
		West Yorkshire	

Source: Addicts Index

As before, aggregate crime trends for the five groups were then calculated. This showed a clear separation, with areas that suffered the interaction of a severe heroin epidemic and high unemployment seeing the largest rises in crime in the early 1990s.

Figure 51: Aggregate burglary trends for five sets of police force areas, grouped by their heroin/unemployment peaks, indexed to 1980/81



Sources: ONS police recorded crime, Addicts Index, NOMIS.

The chart also suggests that of the two factors – heroin and unemployment - heroin may be the more important. The late heroin, early unemployment areas (the green line) clearly have a higher early 1990s peak than the early-heroin, late-unemployment areas (the red line). Figure 51 also suggests that, with the exception of Merseyside, trends since the early 90s have essentially been a reversion to the pre-epidemic level. Areas that saw the biggest crime increases also saw the biggest crime decreases, so that by 2007/08, nearly all areas were back to crime levels similar to those from 1980/81.[87]

Figure 51 also shows that, Merseyside apart, all groups had higher peaks in the early 1990s. This matches the heroin data exactly – recall that even the early heroin forces actually had higher levels of heroin use in the second wave of the epidemic. They are simply marked as early heroin here because they *also* showed some evidence of being affected in the first wave. But the consistently higher 1990s peak does not match the unemployment data, where forces were split roughly half-and-half between those with peaks in the 1980s and those with peaks in the 1990s.[88]

If the interaction between heroin and unemployment is important, it might be expected that the early heroin, early unemployment areas would have the highest crime rises in the early 1980s, which doesn't appear to the case in the chart above. However, changing the date of the indexing (to either the end of the series, or to 1989/90, the start of the second peak) reveals a different picture. See Figures 52 and 53 below:

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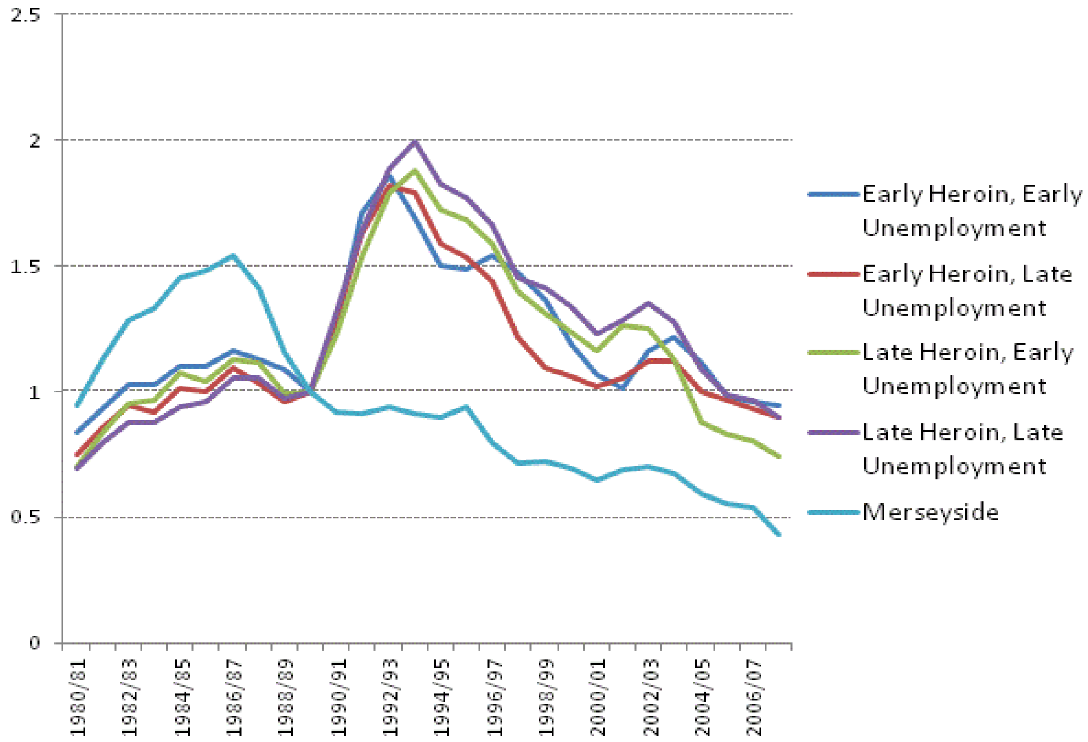
[87] It is possible that Merseyside might show this pattern too if the chart could be taken back far enough. It is very likely that in 1980/81 the heroin epidemic in Merseyside was already underway. Were data available to index Merseyside to other areas at a genuinely pre-epidemic point, it is seems possible that its mid 1980s spike would be larger and hence its trend since

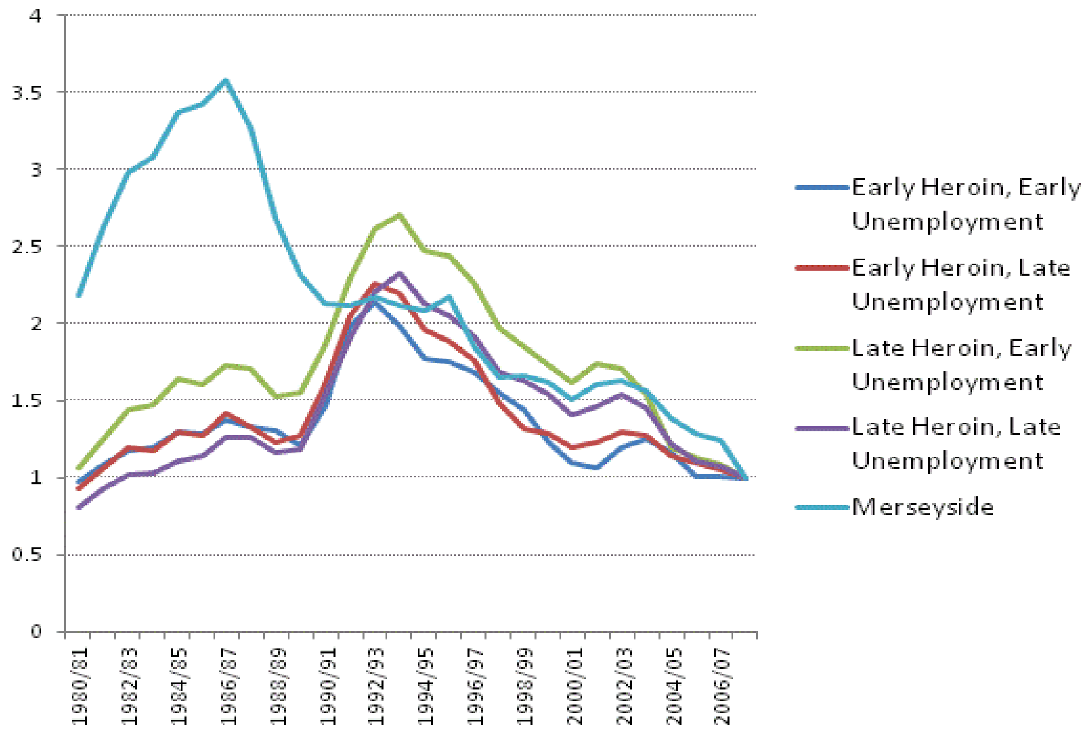
[88]In this light it is also important to note that this analysis effectively weights all forces equally, rather than by the size of their crime volumes.

Figure 52: Aggregate burglary trends for five sets of police force areas, grouped by heroin/unemployment peaks, indexed to 1989/90



Sources: ONS police recorded crime, Addicts Index, NOMIS.

Figure 53: Aggregate burglary trends for five sets of police force areas, grouped by heroin/unemployment peaks, indexed to 2007/08



Sources: ONS police recorded crime, Addicts Index, NOMIS.

These charts suggest a possible interaction during the first epidemic wave as well as the second, though the effect looks marginal for forces other than Merseyside. The entire process was then repeated using theft of vehicle and theft from vehicle data. Results are shown below, with trends indexed to the year at the beginning and end of the series for comparison.

Figure 54: Aggregate theft of vehicle trends for five sets of police force areas, grouped by heroin/unemployment peaks and indexed to different years

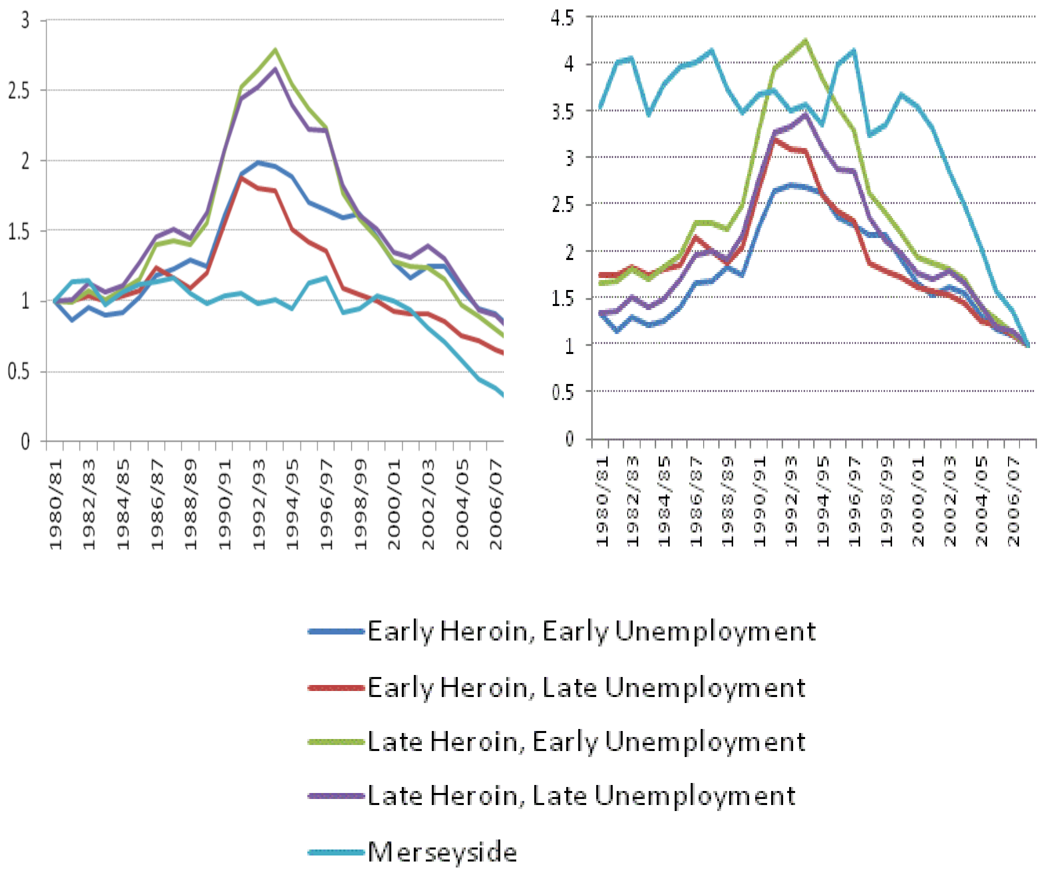
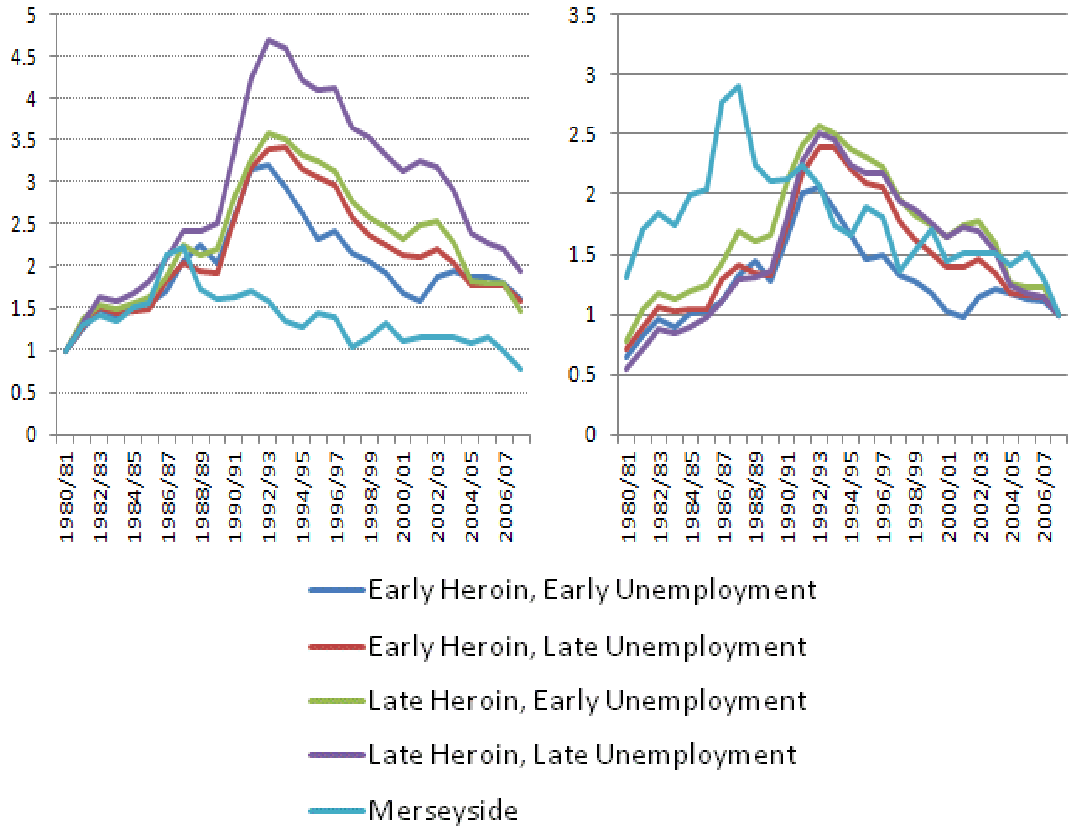


Figure 55: Aggregate theft from vehicle trends for five sets of police force areas, grouped by heroin/unemployment peaks and indexed to different years



Sources: ONS police recorded crime, Addicts Index, NOMIS.

Overall, these charts lend some support to the notion of an interaction effect between opiate/crack use and unemployment on theft *from* vehicle (particularly during the second wave of the epidemic). But there is less clear evidence of an interaction effect on theft *of* vehicle. Figure 54 shows that the theft of vehicle trends for the late heroin groups are similar, and if anything, the `late heroin, early unemployment' group has the sharpest early 1990s rise. Merseyside remains a clear outlier on all the charts, as it does in the heroin data.

<u>Fixed effects regression analysis</u>

In this section all the available data was pooled into a panel dataset and fixed effects regression analysis was carried out to see whether there is within-force correlation between opiate/crack use and crime. The fixed effects technique is widely recognised as one of the best approaches for causal inference when the data is non-experimental, as in this case.[89]

To derive the regression, available evidence from the rest of this paper was used to model system dynamics. Firstly the offending population was divided

[89] See for example: http://www2.sowi.uni-mannheim.de/lsssm/veranst/Panelanalyse.pdf

into two: those who are also regular users of heroin/crack and those who are not. Within each of these two groups a further division was created between those whose offending rate is independent of the economy (i.e. those who do not seek employment even if the unemployment rate improves) and more marginal offenders, for whom the changing nature of the labour market will affect their offending rate. For the heroin/crack group this fits with qualitative evidence showing that for some (but not all) users, the status of the labour market is likely to affect the level of crime they commit. That is, many heroin/crack users do fund their drug use with legal income from employment, so for these individuals, changes in the unemployment rate could make a significant difference to the amount of drug use funded by illegal income.

The following notation is used:

H = heroin/crack users
R = other offenders
N = total population
U = unemployed population

Those that are unaffected by labour market changes are labelled `core' offenders and those who are unaffected are called `marginal' offenders:

Heroin/Crack Offenders (H)		Other Offenders (R)	
Core	Marginal	Core	Marginal

The stock of offenders can then be derived as follows (where p and q are constants reflecting the proportion of heroin/crack users and other offenders respectively, whose offending rate is affected by the labour market:

$$Hp \quad + \quad H(1\text{-}p) \quad + \quad Rq \quad R(1\text{-}q) \qquad \text{(Stock of Offenders)}$$

The rate of offending for each group was then derived. Core individuals offend at a fixed rate regardless of the labour market whereas the offending rate of marginal individuals changes with the unemployment rate (U/N):

$$c \quad + \quad d(U/N) \quad + \quad e \quad f(U/N) \qquad \text{(Offending Rates)}$$

$$Hpc \quad + \quad H(1\text{-}p).d(U/N)+ \quad Rqe \quad Rf(1\text{-}q).(U/N) \qquad \text{(Offences)}$$

It was then assumed that the number of `other offenders' scales with the population size:

$$R = sN$$

Thus, the equation for total offences can be written as:

$$Hpc \quad + \quad H(1\text{-}p).d(U/N)+ \quad sNqe \ + \quad sf(1\text{-}q).U \qquad \text{(Offences)}$$

Grouping constants into single terms, this becomes:

$$B_1H \quad + \quad \beta_2 H(U/N) \quad + \quad \beta_3 N \quad + \quad \beta_4 U \quad + \quad \alpha$$

However, this gives an interaction term in H(U/N) without the individual term (U/N) which is problematic for statistical reasons, hence our final model is:

$$B_1H \quad + \quad \beta_2 H(U/N) \quad + \quad \beta_3 N \quad + \quad \beta_4 U \quad + \quad \beta_5 (U/N) + \quad \alpha$$

In other words, the model includes heroin/crack users in absolute values, unemployment in rates and the interaction between these variables, along with unemployment and population in absolute values. The full panel dataset of 42 police forces in England and Wales contained:[90]

- recorded crime volumes from 1981-1996 for burglary, theft of vehicle and theft from vehicle[91]
- new heroin users from 1981-1996
- total reported heroin users from 1987-1996
- unemployment rate by area from 1983-1996.[92]

The main question of interest is whether the stock of heroin users in a given period influences the level of theft in that period. However, the two heroin variables are both imperfect measures of the stock. The new heroin users variable is essentially a flow variable measuring new additions to the stock rather than total users. But even the total heroin users variable is subject to measurement error of three types. Firstly there is a break in the series in 1986, as discussed. To mitigate this only data from 1987 onwards were used. Secondly, the variable does not capture the total stock of users notified in a given period because it does not include individuals receiving treatment at the beginning of the year who simply stay in treatment throughout the year. But most importantly, only a proportion of users are likely to notify at all.[93] So the variable under-counts reality. The crucial assumption for this analysis then is that the degree of under-counting will not vary significantly across police force areas over time. If the proportion of new and total heroin users captured by the Addicts Index remains constant over time, or at least any change is not correlated with change in the recorded crime levels, it will not bias the estimation, although interpretation of the coefficient becomes less straightforward.

[90] British Transport Police was excluded and due to its small volumes, City of London was combined with the Metropolitan Police service to give a total figure for London.
[91] The data was converted from financial years to calendar years using the following method: 1981 = (0.75 x 1980/81 volume) + (0.25 x 1981/82 volume).
[92] This was derived by dividing the NOMIS claimant count volumes for each police force area by the population estimates for each year, also taken from NOMIS.
[93] This is partly why the new and total heroin users variables cannot be used in a stock-and flow method to calculate each other. i.e. the number of new users in period X added to the number of existing users in period X-1 does not equal the total users in period X. This is partly because there is no measure of out-flow and partly because the total users variable will not include individuals who start the year in treatment and remain in treatment all year without re-notifying.

In general, measurement error of this kind tends to bias results towards zero – i.e. no effect. So to try and mitigate this, an instrumental variable technique was employed – see below. The model was also run with the new users variable in place of the total users variable. Strictly speaking, this is testing a different hypothesis: that the level of crime in an area is affected most by the number of new heroin users rather than the total stock of users. If the coefficient on this variable is significant, it would therefore suggest that the early period of an OCU's drug-using career has the greatest crime impact.[94]

As is standard in these models, police force area level fixed effects and a full set of annual time dummies were also included. Thus our final regression equation is:

$$C_{it} = \alpha_{it} + \beta_1 H_{it} + \beta_2 (U/N)_{it} + \beta_3 U_{it} + \beta_4 N_{it} + \beta_5 H(U/N)_{it} + \eta F_i + \gamma T_t + \varepsilon_{it}$$

Where C represents crime (burglaries, theft of vehicles or theft from vehicles are used); α is a constant; H represents the number of heroin users (where both new and total users were tested, as discussed above); U/N represents the unemployment rate, U represents number of claimants, N is total population, F is a vector of force-level fixed effects, T is a vector of time dummies and ε is a random error term following a normal distribution with mean zero and standard variation $\sigma\text{\^{}}^2$. The subscripts i and t represent the variation by area and time respectively. Simpler variations on this model were also tested, notably without the interaction term, and removing variables that were not significant.

A fixed effects regression using clustered standard errors removes time independent variation between police force areas. The fixed effect will account for underlying differences in the crime propensity between areas as well as drivers which are unlikely to change markedly between areas over the period. The time dummies remove any variation between years which is constant across the country. This should mean that the results are not biased by, for example, the effect of a national-level government crime policy. Clustered standard errors allows for heteroskedasticity between police forces.

A pertinent question is whether sufficient control variables have been included. For the results to be valid there must not be a third factor which influences both heroin use and crime. Some known drivers of crime are unlikely to change heroin use so can be discounted. For example, an increase in alcohol use in an area may increase crime but it is not clear this is likely to drive higher heroin use. Plus, although national consumption of alcohol did increase through this period, the data does not exist (to our knowledge) to see whether there was marked variation between areas over time.

However if a third factor exists, any observed relationship between heroin and crime is invalid. Results will attribute to heroin the relationship between the

[94] It would also capture to an extent the possibility that during the epidemic period in each area, there was also a population of OCUs who initiated at the same time as other users and had a crime impact for the period in which they were using heroin/crack, but who also quit relatively quickly, without ever being notified to the index.

third factor and crime. An increase in unemployment in an area may increase both heroin use and crime. Unemployment data is therefore used as a control variable. Unemployment is also closely related to other crime drivers so controlling for unemployment is likely to control for other economic factors which may drive both crime and heroin addiction. Similarly demographics is likely to influence both the number of heroin users in an area and the amount of crime, so it is also included as a control variable.

Were the data available, other control variables might have been used, particularly numbers of police numbers and numbers of prisoners. However, any resulting bias from the omission of these variables is likely to be small. The use of a fixed effects model removes any third factors which do not change over time. Varying police numbers between areas might conceivably influence both the number of heroin users and crime, but for the most part, increases in police force numbers were shared out nationally in a way proportional to crime. So, increases in numbers are unlikely to vary between areas markedly over time, and the national increase should be controlled for by the time dummies. A national-level increase in the prison population would also be controlled for in the same way.

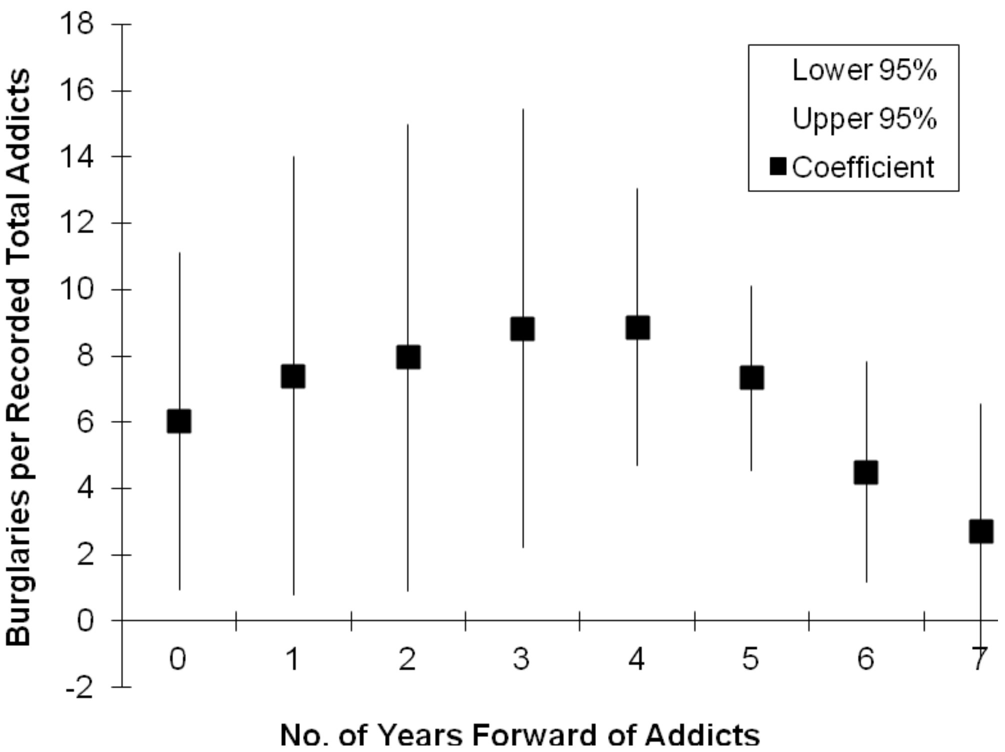
A further problem exists though. As has been much discussed in the rest of this report, the Addicts Index data for new and total heroin users will lag reality because many users will not come to the attention of general practitioners or other medical services for a number of years after the initiation of regular use. More formally, the correct relationship between crime in period t and opiate/crack use (as recorded by the Addicts Index) is likely to involve some function of users reported to the Index in year t and users reported for a number of years after that. For the purposes of the model, the crucial question is to decide the optimal forward-lag to use based on available evidence. A rapid review identified several studies with relevant data. There was general agreement that using a forward-lag is sensible, as the number of users that notified to the Addicts Index or attended treatment in the same year as starting regular use was lower than those who had a lag between the two. For example, in a sample of 8,903 heroin users, only 500 attended treatment within a year and the mean was three years.[95] (Millar *et al*, 2004)

Nordt et al. (2006) find a similar result. And Reuter and Stevens (2007), in their review of Addicts Index trends, agreed that whilst there was a lag, it probably wasn't more than three years for most OCUs. "*Though there is a delay from first year of dependence to first notification, a substantial proportion of those who became dependent were likely within a few years to come into a contact with a physician who might report that dependence*." (ibid.) This also fits with the detailed study of heroin use by Parker *et al*, which estimated that the start of the epidemic in the Wirral occurred between 1980 and 1981, but that the first increases, according to the Addicts Index, occurred in 1982 with the peak in 1983 (Parker *et al*, 1987).

[95] Arguably, the lag between peak-crime and notification could be more complicated because OCUs are unlikely to resort to crime immediately upon starting regular heroin use – they may run down legal sources of income first.

As a result of this evidence, a three-year forward lag was used for the main results, but a two-year and a four-year lag were also tested to show sensitivity. The full findings of this sensitivity analysis are below, but a succinct way to demonstrate that the results are not overly sensitive to the choice of forward-lag is given by the diagram below. This shows the results of a series of fixed effects regressions using burglary as the dependent variable and various forward lags of the total addicts variable as an independent variable along with unemployment, demographics and time dummy controls.[96] It is clear that numerous forward-specifications produced strongly significant relationships. This was repeated for the other crime types and using the new addicts variable with similar results.

Figure 56: Coefficient and 95% confidence intervals for the relationship between burglaries and different years ahead of total heroin users' data



Before reporting the results, the implications of the interaction term between heroin use and unemployment rate requires some elaboration. Our systems dynamics model postulates that the crime effect of heroin use may be exacerbated by a high unemployment rate, as a proportion of OCUs will trade off legal and illegal income. The interaction term tests this proposition. If the coefficient, β_5 , is significant, this would indicate that the upward pressure from

[96] Though the data operates with a lag, this takes the form of a forward specification in the equation as we expect to see a crime increase before we see the Addicts Index variable increase, as the latter lags reality.

an increase in heroin users is worse during periods in which the unemployment rate is high.[97]

In addition, all the results were run with and without London. Crime volumes for London are markedly larger than for other police force areas, so it is possible that a correlation in this area alone could have the effect of making it look like there is correlation across all areas.

Tables 12-14 show the regression results. With each crime type six fixed effects regressions were run. Regressions 1-3 use total heroin users as an independent variable; 1 uses all areas and all variables except the interaction term, 2 is the same as 1 except London is excluded; 3 is the same as 1 except the interaction term is excluded. Regressions 4-6 are exact repeats of 1-3 except new heroin users was used as the drug use variable.

Table 12: Fixed effects regression results for burglary

Burglary	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	8.60** (3.53)	12.42*** (2.60)	8.82 (7.09)			
New heroin users				25.2*** (4.29)	29.8*** (2.78)	16.5 (12.13)
Population Size	0.043 (0.058)	0.066 (0.053)	0.043 (0.065)	0.014 (0.034)	0.021 (0.029)	0.017 (0.036)
Unemployment Rate	626 (696)	-728 (659)	602 (1082)	746 (578)	-459 (579)	1136 (816)
Unemployment Volume	-0.11 (0.039)	0.15*** (0.024)	-0.0078 (0.095)	0.0037 (0.039)	0.14*** (0.031)	-0.48 (0.78)
Interaction term			-0.042 (1.27)			1.73 (2.65)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

Table 13: Fixed effects regression results for theft of vehicle

[97] Note that a high unemployment might also be expected to drive more heroin users. The interaction does not test this, because an increase in users would be captured in the H term. See the conclusion of this section.

Theft of Vehicle	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	4.54 (2.76)	7.25*** (1.20)	2.72 (2.57)			
New heroin users				12.51*** (4.26)	16.1*** (1.87)	6.88* (3.93)
Population Size	-0.11 (0.27)	0.0096 (0.023)	-0.0085 (0.027)	-0.21 (0.023)	-0.006 (0.17)	-0.019 (0.023)
Unemploy ment Rate	-1708*** (600)	-949** (409)	-1514** (666)	-1745** (667)	-784* (372)	-1490 (727)**
Unemploy ment	0.066*** (0.012)	0.029 (0.019)	0.039 (0.033)	0.07*** (0.016)	0.02 (0.02)	0.036 (0.031)
Interaction term			0.35 (0.34)			1.13 (0.74)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

Table 14: Fixed effects regression results for theft from vehicle

Theft from Vehicle	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	10.97*** (1.89)	8.47*** (0.80)	2.39 (2.58)			
New heroin users				24.90*** (5.56)	19.1*** (2.16)	3.74 (8.81)
Population Size	0.039 (0.034)	0.035 (0.35)	0.049* (0.027)	0.0078 (0.028)	0.0086 (0.028)	0.017 (0.026)
Unemploy ment Rate	896* (506)	1574** (583)	1813** (688)	1193** (520)	1856*** (541)	2150** (832)
Unemploy ment	0.024 (0.024)	-0.63** (0.026)	-0.101** (0.040)	0.024 (0.032)	-0.83*** (0.023)	-0.10** (0.051)
Interaction term			1.67*** (0.55)			4.25** (1.81)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

On the whole, there appears to be a strong relationship between the heroin variables on the Addicts Index and recorded acquisitive crime levels. In the specifications without the interaction term, the heroin variables are statistically significant in all but one case (the specification with vehicle crime and total heroin users, and including London). And mostly they are significant to the 1%

level. Including the interaction term sometimes changes the picture slightly, see below.[98]

It is clear from the results that the population term, which was non-significant in every specification, is not adding anything to the model. The results for unemployment are more mixed. Unemployment volume is significant in just two of the six specifications when burglary is the dependent variable, but seems to have a stronger relationship with the two vehicle crimes. However, often just one of the two unemployment variables was significant. So, on the basis that a pared down model is preferable, the regressions were run again without the population term, and with just the most significant of the two unemployment terms. These are the results reported in the short version of the paper and are reproduced below.

Table 15: Final fixed effects regression results for burglary

Burglary	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	8.83*** (3.27)	11.16*** (2.94)	9.07*** (3.22)			
New heroin users				25.2*** (3.95)	29.9*** (2.97)	22.4*** (6.42)
Unemployment Rate	1180 (944)	1711* (944)	972 (952)	983 (909)		858 (678)
Unemployment Volume					0.14*** (0.043)	
Interaction term			-0.054 (0.63)			0.66 (1.84)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

Table 16: Final fixed effects regression results for theft of vehicle

[98] Further checks were undertaken and the results were also robust to changes to specification including removal of control variables, removal of random years and taking natural logs.

Theft of Vehicle	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	4.27	7.11***	0.62			
	(3.01)	(1.18)	(3.12)			
New heroin users				11.6**	15.7***	2.44
				(4.83)	(1.80)	(5.46)
Unemployment Rate			-1209*		-607	-1334**
			(630)		(366)	(650)
Unemployment	0.35**	0.0016		0.032*		
	(0.015)	(0.21)		(0.018)		
Interaction term			0.74***			1.94***
			(0.53)			(0.21)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

Table 17: Final fixed effects regression results for theft from vehicle

Theft from Vehicle	Total Heroin Users (all forces)	Total Heroin Users (exc MPS)	Total Heroin Users (all forces + interaction term)	New heroin users (all forces)	New heroin users (exc MPS)	New heroin users (all forces + interaction term)
Total heroin Users	10.87***	8.96***	7.66***			
	(1.82)	(0.78)	(1.95)			
New heroin users				24.44***	20.5***	16.3***
				(4.89)	(2.29)	(4.82)
Unemployment Rate	1696**	1171*	1320**	1661*	937	1302*
	(506)	(620)	(640)	(866)	(598)	(740)
Unemployment						
Interaction term			0.72***			1.87**
			(0.083)			(0.37)

*** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level
Standard Errors are reported in brackets

Throughout virtually all model specifications, the coefficient on the opiate/crack variable (whether it was total heroin users or new users) was strongly significant. This was particularly true for burglary and theft from vehicle, where all the Addicts Index variables were significant to the 1% level. Interpreting these results is made slightly more complicated due to the forward lag. But to take the relationship between new heroin users and burglary as an example, Table 15 implies that, for each new heroin user notified in a given year, recorded burglary would have been likely to increase by 22-30 offences three years prior to that.

The relationship between heroin use and theft of vehicles appears less strong and is only significant (but strongly so) in the specification without London. One explanation is that according to the Crime Survey of England and Wales, a large proportion of vehicle theft offences at this time involved a vehicle that was subsequently recovered. Hence many may have been motivated by `joy-riding' rather than the monetary gain more linked to illicit drug use. Also, whilst in many areas theft of vehicle showed a similar trend to the other acquisitive crime types, peaking sharply in the early 1990s, in London it did not. In London, theft of vehicle actually declined through the period 1981-1993 while burglary and theft from vehicle rose sharply. So it may be that for most police force areas theft of vehicle offences were linked to the heroin epidemic, but in London, for some reason, they were not.

The results show partial support for a relationship between unemployment and acquisitive crime through the period. Stronger links are found with the vehicle crimes, where there is a significant result for unemployment volume or rate in almost every specification. Generally these are at a lower level of significance than the 1% recorded by the heroin coefficients. The relationship between unemployment and burglary seems less strong, although there are still significant coefficients in the specifications without London.

The unemployment results are interesting in light of the national-level trends outlined in Chapter 2, which showed correlation with crime through the 1980s and 1990s but none during the recent recession. The fixed effects results imply not just correlation during the period 1983-96, but the possibility of causality. This makes it even more puzzling that the 2008 recession and the resulting unemployment rises did not drive up crime. Though there are other potential reasons[99], one possibility is that unemployment has a bigger effect on crime during a period in which heroin/crack use is rising rather than falling. Research suggests that, during periods in which epidemics are taking hold, employment can act both as a preventative factor, deterring opiate/crack initiation or descent into daily use, and as a source of funds, meaning less reliance on illegal income (Pearson, 1987; Henkel, 2011).[100]

The interaction term is an attempt to model the second of these two possibilities (the effect of the first will be incorporated in the heroin use variables[101]). The results are slightly equivocal. There are highly significant results for the two vehicle crimes but not for burglary.

To check the robustness of the results a series of further tests were performed. The first of these investigated whether measurement error within

[99] The most obvious being that the 2008 recession was `different' in some crucial way from earlier recessions, see Chapter 2.

[100] For an interesting, controlled experiment of the effect of simulated unemployment on opioid `seeking' see: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2930063/

[101] If high unemployment drives greater opiate/crack initiation then this effect would be captured by the numbers of users recorded to the Addicts Index. However, given that the Addicts Index counts only a proportion of the true user population it is possible that the significance of the unemployment variables is at least partly due to picking up part of this effect (i.e. anything not captured by the Addicts Index due to measurement error).

the Addicts Index variables biases results downward. To test this, the total heroin users variable was `instrumented' with the new heroin users variable. Both are subject to measurement error however the errors are likely to be different so each measure will pick up a part of the impact of heroin users on crime. Using an instrumental variable approach should uncover the overall impact on crime as the measurement error in each variable is cancelled out. The regression results appear to support this hypothesis as the coefficients are larger than without instrumentation.

Table 18: Results of instrumental variable regressions to check measurement error bias

	Main Model		Instrumental Variable Results	
	Total heroin users (all forces)	Total heroin users (exc MPS)	Total heroin users (all forces)	Total heroin users (exc MPS)
Burglary	8.83*** (3.27)	11.16*** (2.94)	12.69*** (3.20)	14.79*** (2.71)
Theft of vehicle	4.27 (3.01)	7.11*** (1.18)	5.78*** (2.55)	8.36*** (0.75)
Theft from vehicle	10.87*** (1.82)	8.96*** (0.78)	11.78*** (1.33)	10.68*** (0.78)

As expected, the coefficients are uniformly greater under the instrumental variable specification, suggesting that the measurement error is biasing the main model results downwards. It is also noteworthy that the coefficient on theft of vehicles becomes significant in the instrumental variable specification when London is included. It was concluded, therefore, that the main results are – if anything - slightly conservative due to the noise in the Addicts Index data.

Robustness checks for multicollinearity and serial correlation were also performed. Having identified that the heroin variables and unemployment were themselves highly correlated it is important to check that this multicollinearity is not biasing the main results of the model. This was done by running the regressions with and without unemployment variables. The significance and size of the heroin coefficients changed little (within the same 95% confidence interval) depending on whether unemployment was included or not. This indicates multicollinearity is not affecting the result on the heroin variables. Furthermore, although there is a strong correlation (0.7) between heroin and unemployment, the relationship between the deviation from the mean of heroin and unemployment is actually slightly negative, and looking at the variance inflation factor also suggested multicollinearity is not an issue.

Separately, tests showed that there was a high level of serial correlation in the error terms, probably due to the persistence in the crime data. To check whether this was biasing our coefficient estimates, the main fixed effects regressions were re-run with a lagged dependent variable included on the right-hand-side of the equation. The resulting coefficient for lag burglaries was 0.85 (SE 0.094) showing there is certainly serial correlation in burglary. The coefficient on total heroin users was 1.279 (SE 1.79). Multiplying this by 1/(1-0.85) gives a figure of 8.32, which is very similar to the coefficient in the main model (8.83). This suggests that the serial correlation is not biasing the result markedly. However, this specification still had significant serial correlation in the residuals (0.52). So a second lag of the dependent variable was included. This cut the serial correlation in the residuals to -0.14 and the (transformed) coefficient on the total heroin users variable remained comparable to that in the main model at 7.65. It was therefore tentatively concluded that the results are robust to serial correlation issues.

Overall, this analysis suggests that there was a strong relationship between heroin use and crime through the years before and during the crime turning point, a conclusion which is strengthened by the analysis of international trends later in this Chapter. There is also some support for the notion that unemployment played a role and also that high levels of heroin use and unemployment may have interacted to drive up crime even further. However, given the difficulties of the Addicts Index data, these latter conclusions remain tentative. Further tests of these relationships in other areas and time periods would be welcomed.

The coefficients above are difficult to interpret due to the under-counting on the Addicts Index. However, the results do allow for an estimate of the overall percentage of the rise in these recorded crimes, from 1984 to peak in 1993 that was due to the increases in new or total heroin users; and for new heroin users the same can be done for the period 1981-1993.[102] For example, the number of recorded burglaries increased from 693,383 in 1981 to 1,354,282 in 1993. Using the change in the number of new heroin users over the same period (with a three-year forward-lag) and the modelled coefficients (with confidence intervals), the number of extra crimes that the model predicts due to heroin use can be estimated. Dividing this by the total crime increase gives an estimate for the proportion of the rise that was due to heroin. Using this method, it was found with 95% certainty that 9%-60% of the increase in burglaries between 1984 and 1993 can be explained by total heroin users, with a central estimate of 35%. The full results are shown in Table 19 below.

[102] The reason for the slight difference in time periods is due to the break in the Addicts Index data restricting the period we can measure using the total users data.

Table 19: Estimated proportion of the 1981-1993 rise in selected police recorded crime categories explained by the drug use variables

	Burglary	Theft of vehicle	Thefts from vehicle
Proportion of the increase in crime 1984-93 explained by total heroin users	35% (9-60%)	30% (-16-77%)	44% (29-59%)
Proportion of the increase in crime 1981-93 explained by new heroin users	48% (33-63%)	41% (3-80%)	48% (29-68%)
Proportion of the increase in crime 1984-93 explained by total heroin users (Using instrumental variable measurement error-correction approach)	50% (25-74%)	45% (6-84%)	48% (37-58%)

Note: Central estimates are shown with ranges, in brackets, produced from the confidence intervals on the original coefficients.

Although the central estimates for theft of vehicle are in line with the other crime types, the uncertainty around these estimates is much wider and when using total heroin users the estimate is not statistically significantly different from zero. The relationship does become much stronger if London is excluded. Theft of vehicle actually fell in London during this period.

Overall though, the model suggests that opiate/crack use was a significant factor in the large changes in acquisitive crime volumes that occurred across police force areas during this period. Our central estimates suggest opiate/crack use may explain about 40% of the rise in these main acquisitive crime categories.[103]

As a final check the analysis was repeated using different forward-lags on the heroin variables. This produced very comparable results, which are available on request.

Comparing trends with other parts of the British Isles and internationally

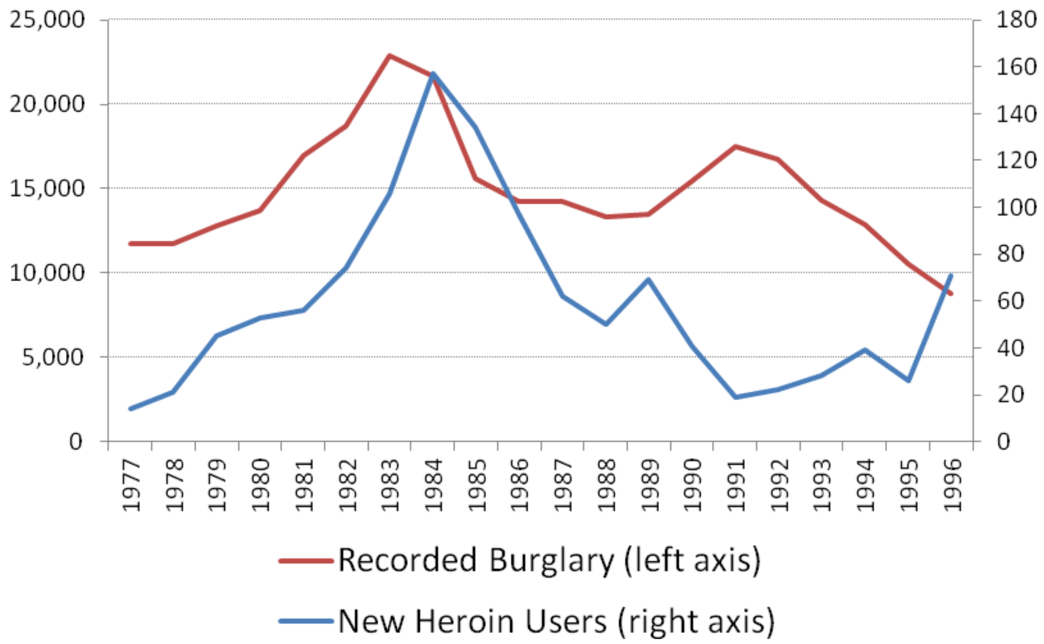
Finally in this chapter, trends in opiate/crack users and trends in crime are compared in other parts of the British Isles and internationally. Though the correlation between opiate/crack use and acquisitive crime throughout

[103] The average of the `proportion of the total rise in crime' estimates for each of the crime types is 41%.

England and Wales appears to be very strong, the data only really contain one area (Merseyside) that followed a noticeably different trend, hence any causal conclusion must remain tentative. Fortunately, Scotland, Northern Ireland and the Republic of Ireland provide further examples of variation.

Evidence suggests that certain areas of Scotland, notably Glasgow, were affected in the very earliest phase of the epidemic. Ditton & Speirits (1981) identify a marked surge in both new heroin users and crime in Glasgow starting in 1979. Edinburgh also seems to have been affected by the epidemic very early in the 1980s. But while the Addicts Index data suggest that Strathclyde, the police force area containing Glasgow, had surges in new users during both waves of the epidemic (peaking in the second wave), the trends in Edinburgh more closely resemble Merseyside. That is, Lothian and Borders – the former police force area containing Edinburgh –appears to have had a large rise in heroin users during the early 1980s but not to have suffered a second wave in the early 1990s. Once again, this was mirrored by the recorded acquisitive crime data (burglary), with a similar 'spike' in the early 1980s.

Figure 57: Recorded burglary and new heroin users in Lothian and Borders police force area, 1977 to 1996[104]



Source: Addicts Index, Scottish recorded crime data.

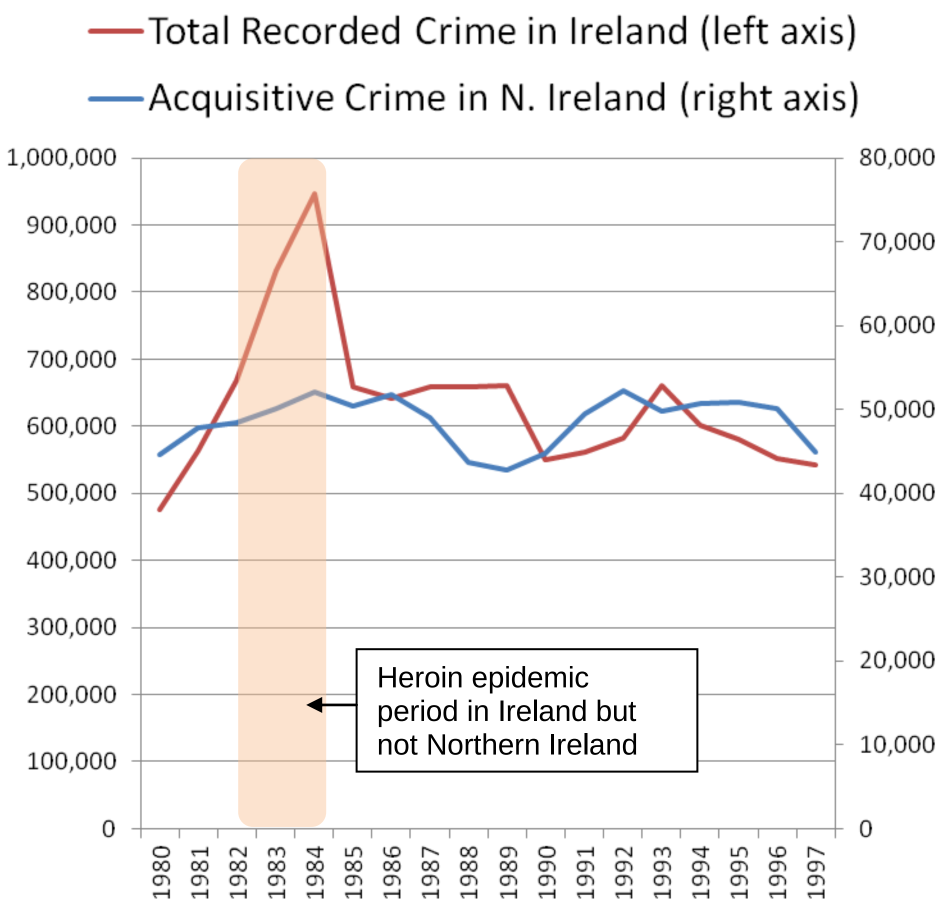
Like Merseyside, Lothian and Borders was an exception to the overall national trend. Total police recorded crime and recorded acquisitive crime for Scotland peaked in 1991. And separately, Ditton and Frischer (2001), using parameters from the US epidemic model, modelled the likely spread of the epidemic

[104] Since the available evidence suggests the Addicts Index has a lagged relationship with crime, the fact it shows a peak in new heroin users a few years *after* the start of the sharp rise in burglary is consistent with the possibility that increases in heroin use drove the increases in crime.

across Scotland. They concluded that the peak in new users occurred around 1991, in line with the peak in total police recorded crime in Scotland.[105]

The Republic of Ireland and Northern Ireland also provide a particularly instructive comparison. Northern Ireland did not appear to suffer a significant heroin epidemic (see McElrath, 2002), whereas the Republic of Ireland did have an epidemic in the early 1980s, confined largely to Dublin (Dean *et al*., 1985). Burglary and total crimes spike very sharply in the Republic of Ireland in line with this epidemic (Figure 58). No spike is visible in Northern Ireland. The overall crime trend remains relatively stable throughout the period.

Figure 58: Crime trends in the Republic of Ireland and Northern Ireland, 1980 to 1997



Sources: Northern Ireland crime data were found here: http://www.psni.police.uk/directory/updates/updates_statistics/update_crime_statistics/updates_crime_statistics_archive.htm . Data for the Republic of Ireland were found here: http://www.crimecouncil.gov.ie/statistics_cri_crime_murder.html

Chapter 2 showed that the US had a peak just over a decade before England and Wales in most if not all acquisitive crime types. It also suffered a heroin epidemic (or series of epidemics) just over a decade earlier. In fact, unlike in

[105] As with most models of OCU trends, their findings are based on various assumptions so should be treated cautiously, but their estimates are similar to those found in a separate Scottish study, focusing on Glasgow (Hutchison *et al*, 2006).

the England and Wales, the US actually had a series of heroin outbreaks throughout the twentieth century, each around a generation apart. But researchers agree that the epidemic that began in the 1960s was by far the most serious. One study (DuPont, 1978) estimated that the number of addicts grew from 50,000 to 500,000 during that decade (and then went on to increase further through the 1970s), which, if true, would be a remarkably similar growth rate to our estimates for England and Wales. Also similar – as noted – was the gradual macro-diffusion of heroin use from the big cities in the vanguard of the outbreak (like New York) to just about everywhere else over a period of several years, such that the highest levels of incidence were probably not reached until somewhere between 1971 and 1977 (Hughes & Rieche, 1995). This would put the US property crime peak (according to the NCVS) squarely in line with the (incidence) peak of the epidemic, exactly as in England and Wales.[106]

What happened next was slightly different from England and Wales, though not for the heroin-using population, which gradually declined through the 1980s and 1990s with a similar cohort effect visible. By 1992 more than half the heroin-related emergency room visits were made by users over the age of 35 Hughes & Rieche, 1995). The difference was in the voracious crack market that developed in the wake of the heroin epidemic in the 1980s, and which changed the nature of the drug-crime relationship in the US in a way that it never did in England and Wales. In short, the relationship probably became more related to violence and less to property crime, and the driver of this was the supply-side rather than the demand side. Indeed, the collective research on the US crack epidemic suggests it was as much an epidemic of suppliers as it was of users (many of the users – as in the UK - were the old heroin cohort diversifying their drug use[107], though many of the new sellers also went on to be users). The sequence has been described by Raskin White and Gorman (2000):

"*There appears to be less economically motivated crime related to crack than there was to heroin abuse in the 1970s and 1980s. The reduction in property crime since the beginning of the crack epidemic supports this view. Because there is more money in crack distribution than in previous illegal drugs markets, drug dealing may have obviated the need to commit property crimes and income-generating violent crimes....As powder cocaine and crack cocaine became popular in the 1980s, the nature of the drug-crime relationship changed. Rates of violent crimes, especially those related to drug distribution and marketing, increased markedly*..." (Raskin White & Gorman, 2000).

[106] It is also worth noting that the slightly later peak in burglary volumes (1979-81 depending on whether we use NCVS or police reports) would be more in line with the prevalence peak, but also it coincided with large rises in unemployment. Generally speaking, across all the nations examined in this paper the combination of high unemployment *and* being in an epidemic state of heroin use seems to drive the largest spikes in crime. High unemployment on its own apparently has far less of an effect.

[107] This is summed up nicely in a review by Kozel & Adams (1986): "*In the earlier period the profile of a heroin addict was a male in their mid to late teens…. In the mid-1980s the heroin addict population still is composed primarily of males but in their early to mid-30s, the majority of whom have a history of heroin abuse that extends back to the late 1960s and early 1970s. They are, in fact, the earlier use cohort*."

Most studies put the peak of crack initiation in the late 1980s (see for example Johnson *et al*, 1994), hence the 1990s saw the decline from peak of the crack epidemic *and* the continued ageing and shrinking of the original heroin cohort. In this light, US crime trends show a strong degree of correlation with drug trends. The acquisitive crime trends tracked the heroin epidemic and the violent crime trends tracked the crack market, meaning perhaps that one of the reasons that `the great crime decline' in the US started in the 1990s was because at that point both markets were falling together.[108] Once again, it should be emphasised here that correlation does not prove causation, and there will almost certainly be other factors playing a role in driving these crime trends, but the degree of correlation is suggestive.

Data on trends in opiate/crack use in Canada are rarer. But one study by Fischer *et al* (1999) does suggest that, like the US, opiate use in Canada peaked far earlier than in England and Wales, which would correlate with Canada's earlier crime peak. The study looked at the age of 114 opiate users in Toronto, who were not in treatment or actively seeking treatment. They found that none of these users were under 20 and just 15% of the sample was aged 21-30. The majority (55%) were aged 31-40 but a sizable minority (27%) were aged 41-50 with 3% aged 50+. This is a reasonably similar age profile to the *current* population of users in England and Wales, indicating that the fastest rates of growth in Canadian heroin use probably occurred around 15 years earlier than in England and Wales, which would fit with the sharp rises in theft seen in Canada to around 1981. It is also worth noting that, despite the ageing cohort of users, the Fischer *et al* study still found that more than two-thirds of the sample admitted to funding their drug use through illegal means and that collectively this was the most important source of income. This lends further evidence to the notion that today's OCU cohort in England and Wales are still likely to be important in relation to overall crime trends, despite their age.

As with Canada, it is harder to get an idea of over-arching OCU trends in Australia. However, several studies suggest that heroin use, like acquisitive crime in Australia, was increasing until around 2001 (Hall *et al*, 2000; Kaya *et al*, 2004; Caulkins *et al,* 2006) and has fallen since. Hospital admissions for opioid use reduced from 6833 in 2000-01 to 4076 in 2004-05 (McKetin, 2006). This fall has been accompanied by the familiar changes in age patterns. The declines in heroin indicators in Australia from 2001 have been particularly prominent in the 15-24 year age group, which has seen a 26% reduction in new enrolments for opioid pharmacotherapy, a 49% reduction in heroin possession/use offences and a 65% decline in heroin–related deaths (Degenhardt *et al*, 2005). Overall then, these data suggest a later epidemic peak than in England and Wales, which fits with Australia's later crime peak.

Europe provides a final example. Figure 10 showed that, in aggregate, crime in Western Europe peaked in the early 1990s and crime in Central and Eastern Europe peaked around a decade later. An almost identical pattern is

[108] Blumstein & Rosenfeld (1997) have pointed out that the violence rise and fall was concentrated amongst younger users, which fits the description of a new cohort of crack seller/users involved in supply-side market violence presented here.

to be found in the spread of heroin across Europe, according to a new set of studies by the European Monitoring Centre for Drugs and Drug Addiction (EMCDDA). These studies have two important conclusions for this analysis. The first is that – in line with the findings presented here – drug use in England and Wales may have peaked earlier than previously thought:

"...*the decline in the number of first-time treatment seekers in England in 2007 would be compatible with decreases in heroin use incidence during the late 1990s*". (Barrio *et al*, 2013).

The second key conclusion is that:

"*the beginning of the heroin use epidemic probably occurred more recently in Central and Eastern European countries than in western ones*." (ibid.).

In other words, the pan-European acquisitive crime trends correlate well with the spread of the heroin epidemic, which clearly occurred later in Central and Eastern Europe than in Western Europe.

To summarise then, there is certainly evidence of correlation between acquisitive crime and heroin-epidemic trends at the local, national and international level. Particularly compelling though is that the narrative of heroin epidemic cycles, almost without exception, seems to offer an explanation for areas that *diverge* from the general trend. Merseyside is the best example within England and Wales. But Edinburgh and its divergence from other Scottish trends; the sharp difference between trends in Northern Ireland and the Republic of Ireland; and the earlier acquisitive crime peak in the US also fit the pattern. Taken together these examples make a reasonably strong case for seeing heroin/crack use as a significant factor in the international crime turning point(s). The next chapter attempts to quantify the effect more precisely for England and Wales.

Chapter 6 – Quantifying the Impact of Opiate/Crack Use on Acquisitive Crime

This chapter seeks to estimate the proportion of the rise and fall in acquisitive crime in England and Wales attributable to the heroin epidemic and its long-term consequences. Due to the data limitations, the model used contains a number of simplifications and assumptions. For that reason, results should be viewed as exploratory. The analysis is really a tentative first attempt, upon which it is hoped others will build.

This technical report includes a detailed description of the methodology behind the model to allow others to follow the steps taken. This is partly in the hope that this might promote the suggestion of new data sources or techniques to improve the model and increase certainty in the findings.

The general approach was:

- to generate estimates for the number of opiate/crack users (OCUs) in England and Wales over time;
- to estimate the average offending rate per OCU per year;
- to multiply these two estimates to give an estimate for the amount of crime generated by opiate/crack use over time.

Estimating the number of OCUs over time

To estimate a trend in OCUs from before the epidemic through to today, a trial-and-error approach was used. The analysis was based around the question: what must the earlier pattern of the epidemic have looked like to result in an OCU cohort of the size and age distribution that exists currently?

To attempt to answer this question a model was built with four key inputs:

- The age distribution of individuals on initiation to opiate/crack use.
- The exit rate (i.e. the rate at which individuals exit the OCU population either through quitting or dying).
- The number of new OCUs each year (i.e. the incidence profile from the period before the epidemic to the current period)
- The number of OCUs in the pre-epidemic period

With these inputs in place it is possible to model the progression of total users throughout the period, along with their age distribution, as these factors flow mechanistically from the above inputs.

The table below describes in brief the approach that was taken to generating the input parameters. Generally, a single parameter (i.e. an assumption) was only used when either the evidence to support that parameter was strong or results were shown not to be very sensitive to that parameter. In cases where these conditions were not met, notably for the profile of new OCUs and the exit rate, either a range of values was modelled or a pure trial end error approach was used. This involved constantly varying the value of the parameter to see which values – in combination with other inputs – produced results that matched the available data on the current OCU cohort.

Table 20: Table showing approach for each model input parameter for creation of OCU trend

Input	Evidence	Sensitivity	Approach
Age of initiation (distribution)	Good	High	Single parameter generated from evidential consensus.
Exit rate	Moderate	High	Use a range of possible exit rates from available evidence.
New OCUs by year from 1975 to 2012	Poor	High	Trial and error. i.e. Start with no pre-conception of parameter.
OCU population pre-epidemic	Poor	Low	Single parameter tested with sensitivity analysis

The next sections run through the generation of each of these input parameters and how they fit together to allow modelling of the entire OCU population.

1) The age distribution of individuals on initiation to heroin/crack use

A literature search revealed two UK papers with such distributions: Donmall *et al*, 2005, and Millar *et al*, 2004[109]. Though there are important differences between the two studies - they cover different time periods, areas and have slightly different definitions of drug use[110] - the distributions produced show a very high degree of similarity, see Figure 59.

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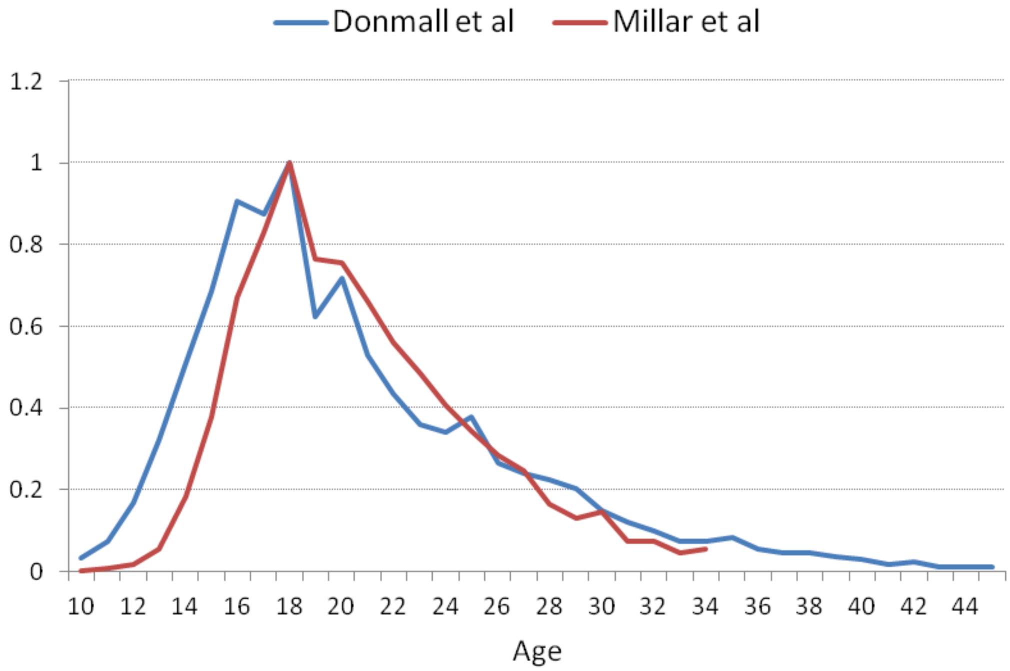
[109] Donmall et al:2005: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/119058/Appendixs5.pdf ; Millar et al, 2004: http://library.npia.police.uk/docs/hordsolr/rdsolr3504.pdf

[110] There are key similarities and differences between the studies. Crucially, both studies use self-reported age of initiation from treatment populations, so the cohort of users who manage to quit before requiring treatment and those who never seek treatment will not be represented. It is possible these cohorts may have different age profiles. The main differences between the two studies are as follows. 1) Millar et al look only at age of first heroin use in a sample of 8903 users, whereas Donmall et al look at age of first use for the drug which they ended up requiring treatment for. In 68% of cases this was heroin but other drugs are included. For example, 9% of the Donmall sample of 140,000 were receiving treatment for cannabis addiction, so the age of first use will relate to that drug. This probably explains why the Millar et al curve (red line above) is much lower than the Donmall et al curve (blue line) at the younger ages. 2) The Donmall et al study uses data from eight of nine Government Office regions hence is quite nationally representative whereas Millar et al use data from Greater Manchester only. 3) Donmall et al use NDTMS records from 2001-2003 (note this is the period in which these individuals registered for treatment and hence self-reported their age of initiation, it is *not* the period of initiation itself; the Millar et al study representations to treatment in Manchester between 1986-2000.

Figure 59: Age of initiation for opiate/crack use

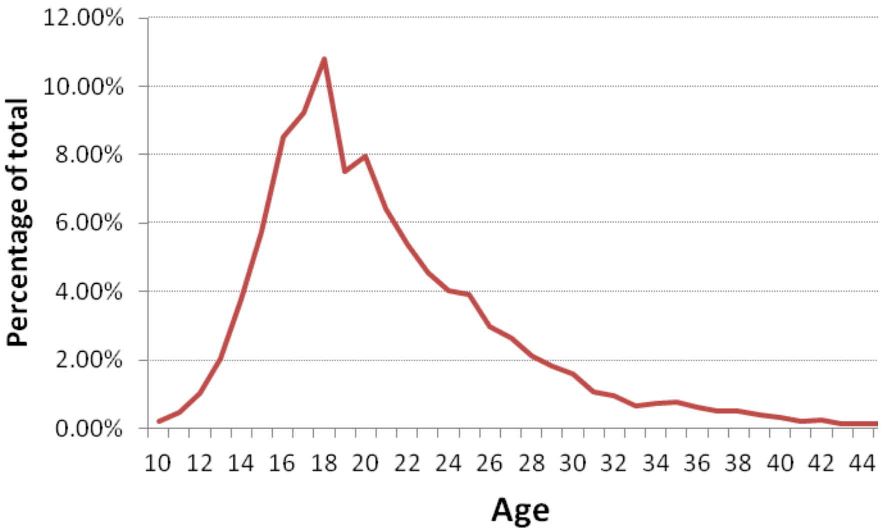


(Note these lines are indexed at the peak age, 18, to allow for comparison).

Sources: Donmall *et al*, 2005, and Millar *et al*, 2004

The results of the two studies were averaged to give an age of initiation curve for use in the model – see below:

Figure 60: Percentage of OCU initiates, by age



Sources: Donmall *et al*, 2005, and Millar *et al*, 2004

So, for each year's intake of new OCUs, the model assumes that their ages are distributed according to the chart above. That is, about 11% are assumed to be 18, and only 1.6% are assumed to be 30.

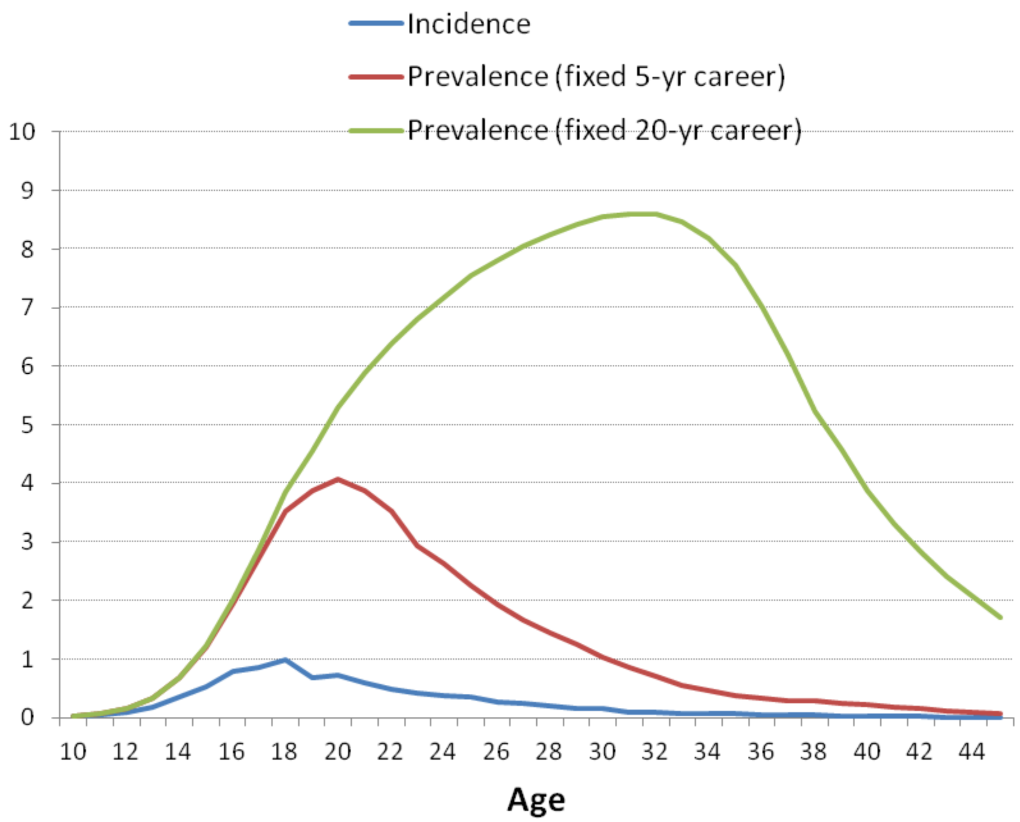
2) <u>The exit rate</u>

The exit rate is necessary to translate the age distribution of new users into an age distribution for the total user population.

The importance of the exit rate can be demonstrated for illustrative purposes by considering a steady-state population – that is, one in which the number of new users (incidence) is the same every year, and assuming a very crude exit rate: one in which all individuals use drugs for a fixed period of time and then quit (or die).

Various estimates have been made for the average length of a heroin/crack-using career ranging from an average of less than six years (Sutton *et al*, 2004) to an average of 20 years (Best, 2006). Generally, treatment samples show longer average career lengths, which is unsurprising seeing as these are likely to be a sub-sample of the most recalcitrant users: those who failed to quit without recourse to treatment. The difference that this can have on steady-state prevalence and the age distribution of the OCU population is demonstrated below:

Figure 61: Effect of length of drug-using-career on OCU population size and age distribution



Note: The scale for the y-axis is arbitrary and flows from indexing the population size at peak initiation age 18 to equal 1. This allows for comparison.

Clearly, the longer the career length, the further the average age of the population moves away from the average age of initiation, and the greater the size of the population.[111]

However, evidence would suggest that a fixed career length is not the most accurate reflection of reality as some users manage to quit very quickly while others continue to use for decades or more (Kaya *et al*, 2004; Sweeting *et al*, 2009; Hser *et al*, 2007). However, there is no consensus on the correct exit rate. De Angelis *et al* (2004), for their modelling of the epidemic peak in England and Wales, use constant exit rates of between 5% and 12%. The latter would imply that in every year, regardless of stage of career, 12% of the OCU population achieve abstinence or die. This formulation is supported by studies like Heyman (2013), which suggest that data best fits the assumption that exit rates are constant for each year of use.

However, other studies suggest that exit rates are not constant by year. Part of the reason for the discrepancy is that it is very difficult to sample OCUs at the point of drug initiation, so those who quit very early are likely to be under-represented. Arguably the only way to tackle this is to look at general population surveys, but these are likely to under-sample more recalcitrant users, who may be less willing or accessible to surveys. For example, Kaya *et al* (2004), using data from the National Drug Strategy Household Survey in Australia, find that more than 60% of all heroin users start and stop in the same year, and only 25% of users had a career length of three years or more.[112]

Another strand of evidence, from US service personnel who served in Vietnam, also suggests that exit rates may be higher in earlier years of use. Studies show that heroin use was widespread whilst in Vietnam, which is perhaps unsurprising given that it was an extreme environment likely to cause

---

[111] It is interesting to note that a very long career length – around 30 years – is required to obtain a population with an average age in the mid-30s, which is what we see in the OCU population today. Obviously though, this situation changes when we move from being in a steady state (i.e. constant numbers of new users) to post-epidemic state in which the number of new users has reduced dramatically from the peak.

[112] An important question is whether those that use opiates and/or crack for relatively short periods of time, say 1-3 years, are relevant to the crime model. That is, do they commit crime commensurate with long-term users for that short period of use? The evidence on this question is sparse, but the little that there is, suggests that they may do. For example, Parker et al (1988) show that the average progression to regular use among a UK sample was just six months, which may imply that even short-term heroin careers might need illegal sources of income to fund them. But even more importantly, longitudinal studies show that `early quitters' had higher frequencies of drug use in the early years of their career than those who went on to have long drug careers (Hser et al, 2001, Best et al, 2006). Furthermore, the longitudinal study of heroin use and offending by Ball et al (1983), found that the rate of offending remained constant regardless of the number of users in each phase. One reading of this is that the users who quit or died before reaching the second period of addiction offended at roughly the same rate as those whose career did progress. The other option is that the more persistent drug users commit higher rates of crime in the first period of addiction, balancing out the lack of crime by the early quitters. Ball et al (1983) specifically analysed this though, and found that – if anything – the reverse was true: individual offending rates for the most persistent individuals tended to increase, very slightly, with each period of addiction. The apparently constant rates of offending were produced by the fact that those who were not represented in the later addiction periods started at very slightly higher rates of offending (ibid.).

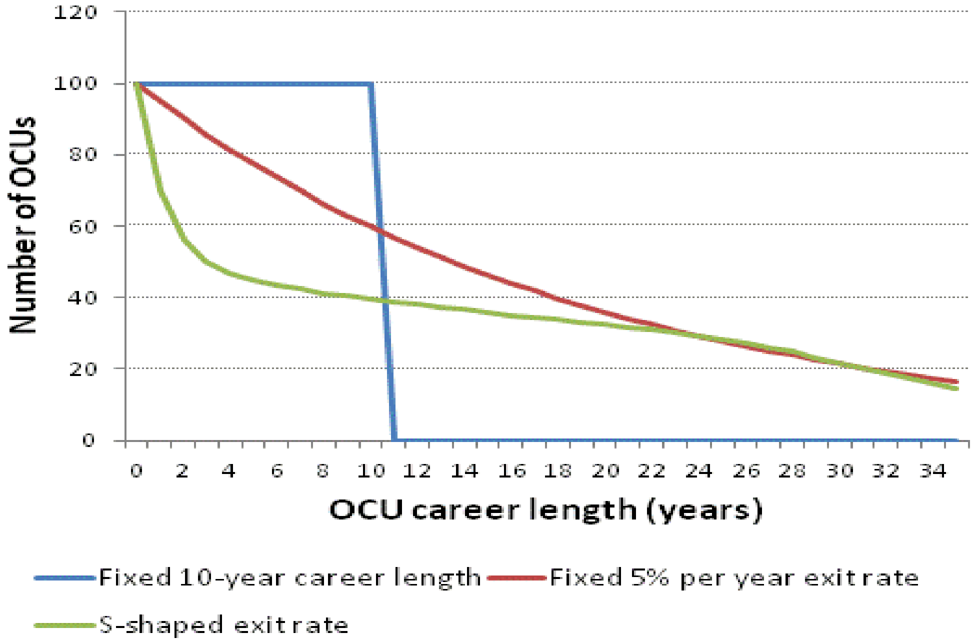
far more individuals to be susceptible than under normal circumstances (Robins *et al*, 1974 and Robins *et al*, 2010). Yet data show that virtually all of those users managed to quit on their return. Only 12% of those addicted in Vietnam were addicted at any point in the three years following return (Robins 1993).

So for the model, a range of exit rates were tested, including fixed per-year rates and s-shaped variations in which newer OCUs had higher exit rates than more established users. For a detailed description of the how the exact exit rates used in the model were calculated, see Appendix 5, which contains a summary of the rapid evidence review conducted on this topic. This review also demonstrated a further factor to take into account: mortality rates for OCUs do not stay constant over the course of drug-using careers. In particular whilst they seem to stay between 1-2% for the first two decades of use, they rise sharply in the third decade, when most users would be over the age of 40.[113] In fact, evidence suggests that in this latter period the exit rate may be more affected by mortality than cessation, and that the former might cause the overall exit rate to increase again. Hence, a couple of variations of this type (labelled `s-shaped exit rates' because of the shape of the survival curve they produce – see Figure 62 below) were also modelled based on actual data from a longitudinal study (Hser *et al*, 2007).[114]

For an illustration of the effect of these exit rate choices, see the chart below, which takes a hypothetical OCU population of 100 users and shows how different exit rates affect the population over time:

[113] This is important currently as many of the current cohort are entering this phase now, implying that mortality rates for the current cohort are likely to increase.
[114] The Hser study followed up users at 11 years, 22 years and 33 years, hence does not allow for exact calculation of exit rates for every year. As such, two different, but plausible options were trialled. Exact figures are available on request.

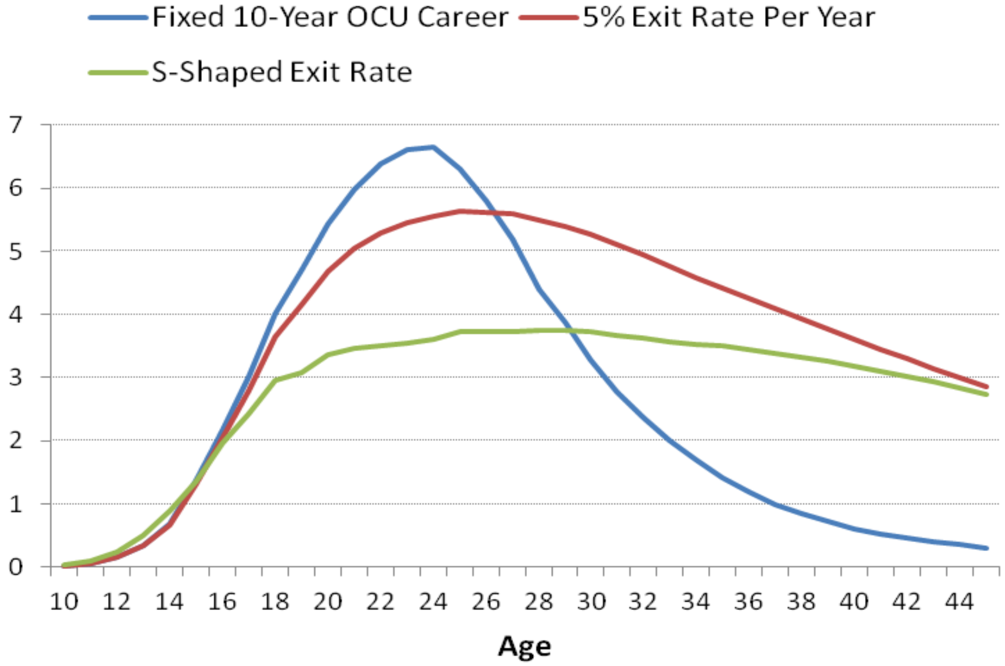
Figure 62: Survival rates for hypothetical OCU population over time, based on exit rate



(The scale for the y-axis has been indexed to population = 100 in year 0 to show how the different exit rates affect the look of the population over time.)

The exit rate has an important effect on the age distribution of the total population, as Figure 63 demonstrates. The naive assumption of a fixed drug-using-career length gives rise to a sharper peak and fewer older users, whereas the fixed exit rate per year and the s-shaped formulations have flatter peaks and mean that some users remain in the population well into their forties:

Figure 63: The effect of different exit rates on OCU prevalence in a steady state[115]



Note: The scale for the y-axis is arbitrary and flows from indexing the population size at peak initiation age 18 to equal 1. This allows for comparison.

As a final summary, Table 21 below shows the different exit rates that were modelled as part of the trial and error process, with a brief description.

Table 21: Exit rates used in the model

Exit rate		Description
5%	Fixed	A given percentage of users exit the population each year, regardless of stage in opiate-crack using career
6%	Fixed	
7%	Fixed	
8%	Fixed	
9%	Fixed	
10%	Fixed	
11%	Fixed	
12%	Fixed	
13%	Fixed	
30%	reducing by 10%	Exit rates start high early in career and reduce by fixed percentage each year
30%	reducing by 15%	
30%	reducing by 20%	
Hser-based 1		S-shaped exit rate, based on actual data
Hser-based 2		

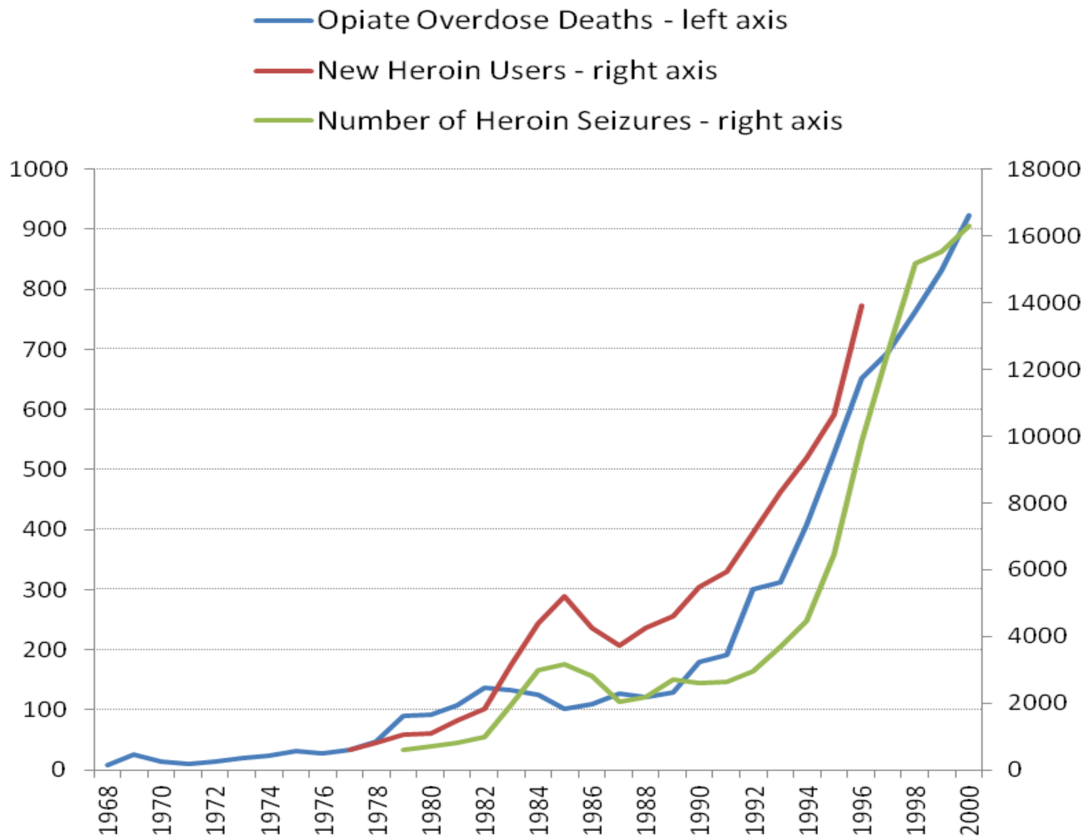
[115] It is important to note that the x-axis in this chart is age, not time. All the curves assume a constant prevalence over time. So the sharpness of the peaks in Figure 63 is not an indication of the sharpness of the peak over time that would be driven by each of these exit rates during an epidemic.

3) <u>The number of new OCUs from 1975-2012</u>

The exit rate allows for modelling of the entire population given a certain number of new users per year. This section outlines the method for deciding how many new users there were in each year from 1975 to the present. The year 1975 was chosen so that the time period covered by the model definitely started before the epidemic began (see Chapter 3).

To attempt this, data on a range of available indicators were gathered. The only data sources that could be identified for the 1980s and 1990s were the Addicts Index; data on drug deaths and data on drug seizures.[116] These are shown below in Figure 64. Clearly there is a fair amount of agreement between indicators, in terms of the scale of the epidemic increase.

Figure 64: Available Indicators Showing the Magnitude of the Heroin Epidemic



Sources: Addicts Index for new heroin users; Home Office statistics for seizures and http://aje.oxfordjournals.org/content/160/10/994.full.pdf for opiate overdose figures).

The indicators suggest that growth was non-linear. That is, during the epidemic period, growth was greater than simply adding a constant amount of new users each year.

[116] Data were also gathered data from the Regional Drug Misuse Databases which run through the late 1990s; from the Hay et al capture/recapture estimates of OCU prevalence (including the hidden population) in the from 2004 onwards; and from the Drugs Data Warehouse which incorporates data from the National Drug Treatment Monitoring System (NDTMS) and various Criminal Justice System sources of data on drug users.

However, there are three major problems with these indicators:

i) All three are likely to lag the true rise in heroin/crack use. The Addicts Index lag has been much discussed already, but evidence also suggests that overdose deaths are less likely in the first phase of heroin/crack use (Hickman *et al*, 2003), and seizures represent the enforcement response to the heroin epidemic; which obviously implies a time lag of some degree.[117]

ii) The lag will not be discrete. That is, it is not the case that every OCU will simply wait a given number of years before being notified to the Addicts Index or suffering an overdose. Some may actually visit a GP almost immediately but many will never visit one at all. These occurrences will follow distributions of their own. In other words, the sharp rises in the original datasets from about 1980 probably *do* represent (more or less) the start of the epidemic, because the indicators would rise immediately due to the small percentage of users that *will* seek medical help immediately, or die of a drug overdose. What the indicators will do though, is underestimate the growth in the population during this initial period because the majority of users will not appear on the indicators until later in their drug-using careers (if at all).

iii) As the Addicts Index data was discontinued after 1996 and both the other indicators really measure prevalence (indirectly) rather than incidence, there is no real indication of how fast new users might have decreased once the epidemic peak was reached.

So, rather than assume an incidence profile based on weak evidence, a pure trial-and-error method was employed. What this means in practice is described below in the section on the modelling process, scoring and results.

4) <u>The number of OCUs in the pre-epidemic period</u>.

The final input parameter required was an estimate for the size of the OCU population in 1975, pre-epidemic. Estimating the OCU population in this period is not easy, as data is sparse. However, sensitivity analysis (see below) showed that final results were not that sensitive to this parameter. So rather than adopt a trial and error approach, a single value was selected based on the only evidence available for that period, the Addicts Index.

The number of new notifications to the Addicts Index for 1975 was 926. This will be an under-count for reasons explained above, but it will not be under-counted by as much as the prevalence estimates, which experts have suggested under-count by a factor of somewhere between three and ten (Parker & Newcombe, 1987; Strang *et al*, 1994). So an under-count factor of two was assumed for the incidence count and the result was then rounded to the nearest thousand to avoid spurious accuracy, giving a 1975 OCU

[117] The fact that heroin seizures go on increasing well into the 2000s when all other indicators show that use must be falling, suggests that there must be a lag of some description.

incidence of 2000. Under sensible exit rate assumptions and assuming an endemic state (i.e. a steady incidence rate) this produced a total 1975 population of around 15,000 OCUs. This was the value used in the model, though sensitivity analysis was conducted.

5) The modelling process, scoring, and results

The input parameters drive the calculations for prevalence (which is simply a function of the number of new users coupled with how long the existing users stay being users) and for the age distribution (which is simply a function of the age of users at initiation and how long they typically stay being users). Each of these can be calculated for every subsequent year in the model (up to the present and projected into the future) provided there is a figure for the number of new users in each year.

But as discussed, some of the input parameters were not fixed, they were either a range (the exit rate) or completely unknown (the incidence profile). So to decide on the best estimates for these parameters, a trial and error approach was employed. In each case, one of the exit rates was selected from the list in Table 21 and combined with an incidence profile. This was then `scored' by judging how closely the cohort it produced matched current estimates for the size and age of the OCU population, as described below. The incidence profile was then adjusted until the score was improved. Once the score could no longer be improved, the process ended and results recorded. A new exit rate was then selected and the process repeated.

The scoring was based on how well results fitted with OCU population data from 2005 onwards. Each specification was checked against two criteria:

1) ***Size of OCU population in 2004-11***: using the annual published estimates in Hay *et al* (2012).[118]
2) ***The age distribution of the population in 2008***: as given by the DDW. (See Figure 65 below).[119]

This was done by minimising the sum of squared residuals – i.e. by minimising the `gap' between the modelled results and the actual ones. By this process a likely range of values for the epidemic peak; and population size at the peak, were established. The results of this process are shown below:

[118] The Hay *et al* estimates are only for England, not England and Wales. However, in the last year that the Addicts Index measured total heroin users (1996), Wales only had 572, around 2% of the total for the total for England which had more than 27,000. Given that adding this percentage on to the totals in the Hay et al estimates would not raise them out of their current confidence intervals, the decision was taken not to try and adjust the results for Wales in the modelling. If anything this makes the estimates in that chapter more conservative. Sensitivity analysis on these numbers was also conducted.
[119] This is the age distribution as of Jan 1, 2008 of all individuals identified on the DDW as opiate/crack users either due to seeking treatment for these problems, testing positive for opiates (positive cocaine testers were excluded as the test does not distinguish crack from powder cocaine) or who were on the probation dataset and identified as heroin/crack users.

Table 22: Modelling results for estimating the number of new and total OCUs over time

Exit rate		Incidence		Prevalence		Score (lowest = best)
		Peak	Value	Peak	Value	
5%	Fixed	1994	36,416	1999	383,810	43.7
6%	Fixed	1994	42,813	1998	410,381	58.1
7%	Fixed	1993	56,797	1997	481,372	82.1
8%	Fixed	1992	62,383	1997	496,481	85.9
9%	Fixed	1992	75,612	1997	559,286	100.7
10%	Fixed	1992	94,600	1996	686,826	127.2
11%	Fixed	1992	117,219	1995	792,211	144.2
12%	Fixed	1991	137,181	1995	842,158	158.3
13%	Fixed	1991	160,090	1995	941,155	216.5
30%	reducing by 10%	1993	239,097	1997	869,657	122.6
30%	reducing by 15%	1994	125,535	1998	543,887	54.9
30%	reducing by 20%	1994	104,234	1998	428,699	54.3
Hser-based 1		1993	103,635	1998	493,730	54.9
Hser-based 2		1993	103,187	1998	478,660	52.2

From this table, the following conclusions were drawn:

- Incidence probably peaked between 1991 and 1996 and declined sharply thereafter. (The table suggests 1991 to 1994 but the range is broadened due to the `solver' results explained in Appendix 9).

- Prevalence probably peaked between 1995 and 1999.

- The exit rate for the population in the years 2005-11 may be quite low. Certainly, better results (lower totals in the final column) seem to arise from the specifications with lower exit rates. This is driven by the fact that the Hay *et al* OCU population estimates show only gradual decreases and the DDW suggests few young users in the population.

- However, formulations in which the exit rate starts high but decreases over time, or is slightly s-shaped (the final five rows) score about as well as having low quit rates throughout, implying these may be the most likely in reality, given that a 5% quit rate throughout would contradict studies like Kaya *et al* (2004) and the Vietnam evidence.

- Given these conclusions, it is probably fair to say that at the epidemic peak there were likely to be between 400,000 and 550,000 OCUs.

Clearly, there is the possibility for human error or bias in this trial and error process. But to check for this, a separate set of results were computed using the Excel solver tool rather than the iteration process, see Appendix 9. These suggested an incidence peak between 1995 and 1997 and a prevalence peak in 1998. They also corroborated the very sharp drop in new users in the second half of the 1990s.

Based on the evidence above, the “Hser-Based 2” formulation was selected for the final model as it matched the observed data very closely (i.e. it had a very low score – the second lowest) and is in line with evidence on higher exit rates in the early years of career. But other options are tested as part of sensitivity analysis.

To illustrate how well the Hser-Based 2 estimate matches up to our two real-life data tests, see the graphs below:

Figure 65: Comparison between modelled results and the actual Drugs Data Warehouse data for the age distribution of the opiate/crack user population in 2008

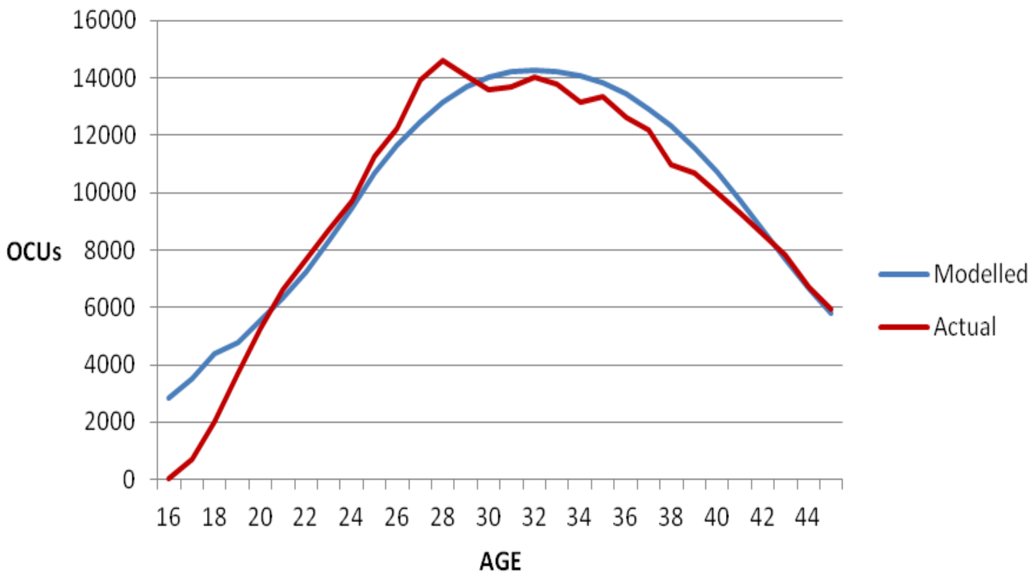
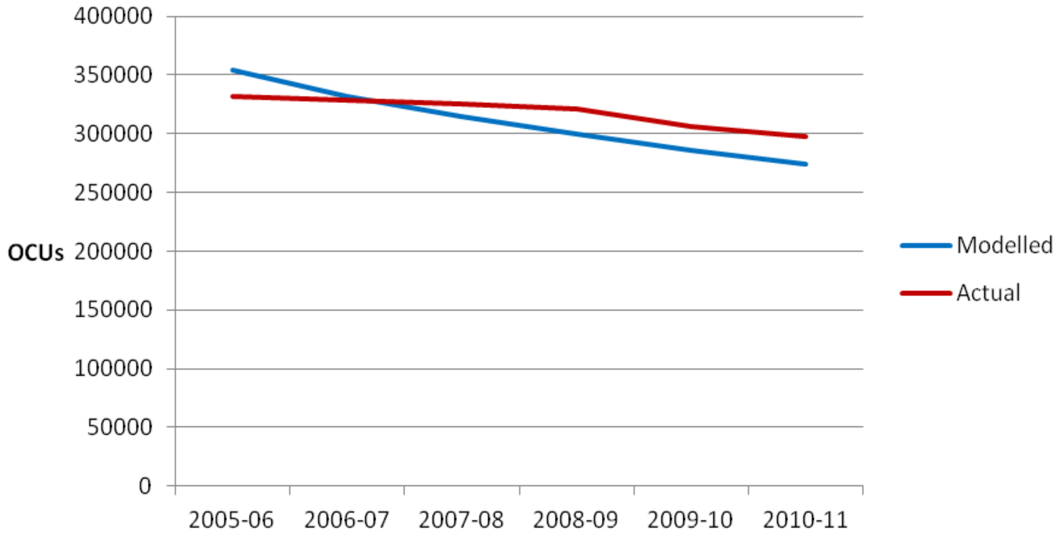
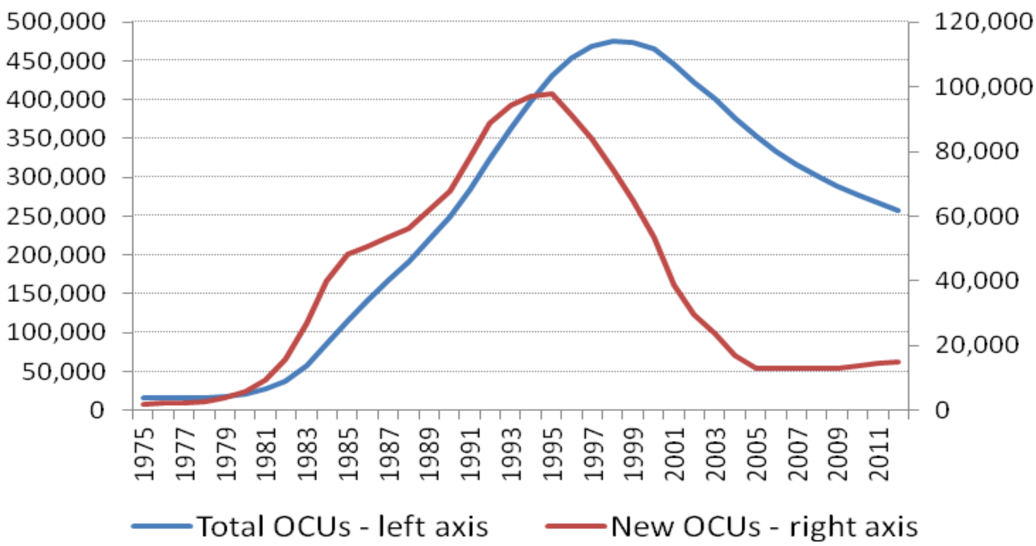


Figure 66: Comparison between modelled results and the Hay *et al*. estimates for the opiate/crack user population between 2005/06 and 2010/11



The resulting trend in new and total OCUs that this produces, and which was used in the final model, is shown below (note that the two are measured on different axes to clearly show the shape of both curves even though their levels differ markedly):

Figure 67: Modelled trend in new and total OCUs



Estimating the crime rate per OCU per year

The studies used for the crime part of the model were gathered via a non-systematic literature review. Any study that gave an indication of the volume of offences committed by a cohort of OCUs was used. The full results of this search are detailed in Appendix 4.

Many of these studies used self-reported offending (which has been shown to be a generally accurate measure of capturing total offending by drug-using populations, see Jarvis & Parker 1989; Manzoni *et al*, 2006).[120] But some used number of official arrests and/or convictions. Most used simple counts of offences but these were often broken down into different categories – for example some studies just counted "thefts" while others broke that down into shoplifting, thefts from vehicles etc. Some studies didn't use offence counts at all but "days involved with crime" or some other measure.

The studies also differed in their location. Most were from the US or UK, but the list also includes studies from Australia, the Netherlands, Norway etc. They also differed in terms of the cohort being studied. Many used treatment as a tool to recruit drug-users to the sample and crime counts were taken from individuals pre- and post-treatment. Another group of studies used samples of arrestees who had self-reported opiate/crack use. Some studies tried to sample the "hidden population" of drug users. i.e. those who do not feature in treatment or arrestee samples. The most common method for this was via "snowball" techniques that involve gathering a sample of OCUs by using peer networks – i.e. asking OCUs whether they can approach fellow OCUs in the community to also agree to being interviewed for the purposes of the research.

Whilst it is not easy to directly compare the results from all the studies, given the different settings and methods, there is a reasonable level of agreement in the *magnitude* of crime admitted to, or associated with, OCU cohorts. This is true across nations and across cohort-types. Some more tentative conclusions are that:

i) arrestee cohorts seem to commit more crime than treatment cohorts, as might be expected,
ii) all cohorts commit a wide range of acquisitive crimes, but commit fewer violence offences
iii) studies that attempted to access the hidden population still reported comparable volumes of crime to those from treatment or arrestee cohorts;
iv) finally, there is some suggestion of a trend towards older studies reporting higher volumes of crime and more serious types of crime. For example, in the UK studies, burglary seemed to be a very prominent part of OCU offending in the 1980s, but was less so in more recent studies.

[120] But also note that a few studies have questioned this – see Bukten 2012 for a summary.

The long-list was whittled down to a short-list including only studies that used UK cohorts and self-report data with offending breakdowns that could be mapped onto the CSEW. Self-report data was used as evidence demonstrates that it best captures the concentration of offending among a small proportion of individuals (Farrington *et al*, 2006).

The short-list also allowed two approaches to the problem of extrapolation. This problem arises because the two most common cohorts from the studies measuring criminality are treatment-seekers and arrestees. These are sub-sets of the total OCU population and may not be representative of the population as a whole (despite point iii above). Hence, care must be taken not to extrapolate the amount of crime committed by these cohorts to the entire population; something for which studies of this type have been criticised for previously (Stevens, 2008).[121]

So to ensure that offending rates were only applied to suitable samples of OCUs, two separate methodologies were used. This has the added advantage of allowing for triangulation of results:

> <u>Treatment approach</u>: offending rates were calculated for OCUs in and out of treatment (using pre-and–post treatment studies) and other evidence was used to divide the OCU trend over time between those in treatment and those out of treatment. The higher out-of-treatment offending rate was therefore only applied to the latter proportion.
>
> <u>Arrestee approach</u>: offending rates were calculated from arrestee surveys for OCUs who get arrested in a given year. A separate rate was calculated from a general population survey for OCUs that do not get arrested in a given year. Separate evidence was used to divide the OCU population over time into these two groups, then the different offending rates were multiplied by the respective numbers in each.
>
> <u>Establishing offending rates for OCUs in and out of treatment</u>

Three treatment-based studies were shortlisted: The National Treatment Outcome Research Study (NTORS), The Drug Treatment Outcome Research Study (DTORS) and Coid *et al*, 2000.

A full description of these studies, and the offending levels of the cohorts, is contained in Appendix 6. This also discusses how cohort offending volumes were converted into annual rates of offending per-OCU, as shown in Table 23 below, which has the rates for pre-treatment cohorts:

[121] There are good reasons for expecting the hidden population of users to be different – in terms of their level of criminality – to users from treatment or arrestee surveys. It is certainly true that more law-abiding drug users would be likely to be in this group, but it also possible that the most chaotic – those who would refuse to take part in any survey – would also be in this group. Given that – as we have seen – crime volumes are almost always dependent on a small proportion of the most prolific offenders, this fact should not be ignored.

Table 23: Average offending rates pre-treatment, all crimes

Average number of self-reported crimes per OCU per year, pre-treatment					
NTORS		**DTORS**		**COID**	
Shoplifting	79.9	Shoplifting	48.4	Theft/shoplifting	73.1
Fraud	12.1	Theft of a vehicle	0.7	Dealing	56.8
Burglary	4.8	Theft from a vehicle	2.0	Fraud	8.9
Robbery	1.5	House burglary	0.4	Burglary	7.2
Other Theft	5.1	Business burglary	2.5	Violence	3.6
		Robbery	0.8	Benefit fraud	53.9
		Bag snatch	0.9	Vandalism	0.1
		Cheque or credit card fraud	1.0	Other	21.1
		Begging	6.1	Robbery	1.5
		Buying and selling stolen goods	31.7	Prostitution	11.9
		Drug dealing	27.8		
		Prostitution	6.4		
		Other stealing	5.0		
		Other violent crime	1.4		
Total	**103.4**	**Total**	**135.0**	**Total**	**238.1**

It made little sense to compare total offending per-OCU from each study as some included more crime types than others. So crime types not recorded in all three studies were excluded; and other categories were grouped together to allow for comparability. The results of this process are shown in Table 24 below:

Table 24: Average offending rates pre-treatment, comparable sub-set of crimes

Comparable self-reported crimes per year (pre-Treatment)					
NTORS		**DTORS**		**COID**	
Shoplifting	79.9	Shoplifting	48.4	Shoplifting component of theft/shoplifting	68.7
Fraud	12.1	Cheque or credit card fraud	1.0	Fraud	8.9
Burglary	4.8	House + business Burglary	2.9	Burglary	7.2
Robbery	1.5	Robbery	0.8	Robbery	1.5
Other theft	5.1	Theft of and from vehicle + bag snatch + other stealing	8.5	Theft component of theft/shoplifting	4.4
Total	**103.4**	**Total**	**61.5**	**Total**	**90.7**

The only process contained within the table above that involves more than a simple addition of categories is the separation of the theft/shoplifting components of the Coid *et al* (2000) study. This was achieved by presuming that the breakdown of the theft/shoplifting category was similar to the breakdown between other theft and shoplifting in NTORS (which would suggest that 94% of this category was shoplifting and 6% was theft).[122]

Looking at the results, the DTORS total is noticeably smaller than the others, possibly because DTORS chose to exclude high-offending outliers as discussed in Appendix 6. However, as the table below demonstrates, this difference disappeared when the comparable crimes were restricted to those that would be picked up by the CSEW.[123] See Table 25 below.

[122] Note that using DTORS would give a much higher proportion of theft, around 11%, so again the approach we have taken is conservative.
[123] This is possibly because the high-offending outliers tend to report very large volumes of shoplifting offences.

Table 25: Average offending rates pre-treatment, CSEW comparable crimes

Comparable BCS/CSEW self-reported crimes per year (pre-treatment)						
BCS/CSEW category	**NTORS**		**DTORS**		**COID**	
Domestic burglary	Burglary with business burglary removed	2.0	House burglary	0.4	Burglary with business burglary removed	3.0
Robbery	Personal robbery	1.3	Personal robbery	0.7	Personal robbery	1.4
Other acquisitive	Other theft	5.1	Theft of and from vehicles + bag snatch + other stealing	8.5	Theft component of theft/shoplifting	4.4
Total	**Total**	**8.4**	**Total**	**9.6**	**Total**	**8.7**

This table was created by removing commercial crimes and fraud from the previous results.[124] Reassuringly, the overall results for the three sources are

[124] For robbery and burglary it was necessary in some cases to estimate the split between commercially-targeted and non- commercially targeted offences. To establish a sensible estimate for the burglary split we isolated papers that split overall OCU burglary offending between the two categories. Three studies were found that had a split: the Wirral studies of the 1980s by Parker et al, which found that 74% of burglaries were domestic burglaries; the Arrestee Survey, which produced an estimate of 35-37% of burglaries being domestic; and DTORs in which only 14% of burglaries were domestic. There are very large discrepancies between these estimates. One possible explanation is based on the different time periods of the studies. The Wirral studies were conducted in the 1980s when the general level of house security was lower (as suggested by the improved housing security measures recorded on the British Crime Survey through the 1990s). So drug users may have targeted residential properties more in the early days of the epidemic and switched to commercial properties in the later periods (both the Arrestee Survey and DTORs were in the 2000s) as residential security improved. This type of change over time is an inherent weakness of models of this type, but note that in this case, by using an average of the three estimates, 41%, we are essentially being conservative about the effect on the overall CSEW crime trend (if the time hypothesis is the correct one). This is because an average would *under*-estimate the rise in burglary recorded by the survey in the early phase of the epidemic, but also under-estimate the fall (as in reality the fall might be compounded by a switch into commercial burglaries not recorded by the CSEW). The split on overall police recorded crime between domestic and commercial burglary is 49% domestic burglary, 51% commercial according to the figures for the year ending December 2012, and this has changed little over time (in 1980 domestic burglary comprised 48% of all burglary). Either way, using 41% looks like a moderately conservative estimate.
No studies could be located that specifically asked OCUs about the split between personal and commercial robbery offending, so the split on recorded crime has been applied, which shows that personal robbery accounts for about 90% of all robbery. Hence the totals for robbery were simply multiplied by 0.9.

quite close together. The same process was repeated for the in-treatment offending rates (Table 26).

Table 26: Average offending rates in-treatment, CSEW comparable crimes

Comparable BCS/CSEW self-reported crimes per year (in-treatment)						
BCS/CSEW category	**NTORS**		**DTORS**		**COID**	
Domestic burglary	Burglary with business burglary removed	1.17	House burglary	0.24	Burglary with business burglary removed	1.59
Robbery	Personal Robbery	0.77	Personal Robbery	0.47	Personal Robbery	0.65
Other Acquisitive	Other Theft	2.98	Theft of and from vehicles + bag snatch + other stealing	5.69	Theft component of theft/shoplifting	3.06
Total	**Total**	**4.92**	**Total**	**6.40**	**Total**	**5.30**

The estimated offending rate used in the modelling was the simple average of all three studies (5.54). Thus, final CSEW (acquisitive crime) offending rates for the model were 8.96 when not in treatment and 5.54 when in treatment.

Though the primary focus of this study is not the effectiveness of treatment, the validity of the `treatment effect' used here requires brief comment. The modelling assumes that those in treatment offend at a rate approximately 38% lower than those not in treatment. The first thing to point out is that the three studies used in the analysis all have limitations, as discussed in Appendix 6. The main ones are set out in the table below:

Table 27: Limitations of treatment studies used

	Control	Nationally representative	Retention rate[125]	Excluded outliers	% OCUs
NTORS	No	(Yes)	83% (though compensated by using convictions data)	No	Around 90-95%
DTORS	No	Yes	63% (though data weighted to compensate)	Yes	Around 85%
Coid *et al*, 2001	No	No	70%	No	100%

Most importantly, none of the studies has a robust control group, meaning that the reductions in offending cannot be attributed to the treatment with any great confidence.

However, for the purposes of this paper, this limitation may be less important than some of the others. For the model, the point of interest is whether OCUs in active engagement with treatment offend at lower rates than those who are not engaged with treatment. All evidence suggests they do. It does not matter, for the model, whether treatment is the sole *cause* of this drop in offending rates. In other words, what's really being captured via `the treatment effect' here is the periods in which OCUs would still be classed as OCUs but during which they will be committing less crime. Research consistently shows that as OCUs progress through their career they typically have many periods of recovery or semi-recovery in which drug use and offending levels are considerably lower (Ball *et al*, 1983, Nurco, *et al*, 1985; Bukten *et al* 2013) Whether or not these are directly caused by treatment (or are more a function of the OCUs own motivation to change, for example) is an important issue of course, but it is not relevant to this model.[126]

Of more concern are the other limitations of these studies. Exclusion of outliers and the fact that not all the participants were OCUs would be likely to make the estimates conservative, but attrition (that is, loss of participants in successive waves of data collection) would have the opposite effect. If the

[125] The retention rate is the proportion of participants retained over the period of the data collections. So a retention rate of 83% means that 17% of the sample were not followed up.

[126] Here the question of whether or not an OCU who was stabilised by treatment at a lower (or even abstinent) level of drug use would be counted as an OCU in the official figures, is relevant. If not, then it would be incorrect to include any `in-treatment' reductions of this type. However, it is clear that a substantial proportion (around two-thirds) of the current OCU population is in contact with treatment, many of them receiving regular methadone. There is also evidence to suggest that even in periods of greater stability and treatment, OCUs may continue to use (potentially smaller amounts of) heroin and/or crack alongside methadone maintenance (Leri et al, 2002; Bloor et al, 2008). The assumption made here is that the lower post-treatment level of offending is justified for this group, who will make up the majority of OCUs in the current cohort..

most chaotic drug users are lost to follow-up – which seems plausible – then the treatment effect may be over-exaggerated. However, DTORS attempted to compensate for this by using weights. And this paper removes that bias from the NTORS results by using the crime reductions from the convictions data rather than the self-report (see Appendix 6).[127] The fact that the Coid *et al* study was not nationally representative is another concern, but it had very similar findings to the other two and excluding it would therefore not change the results in any significant way.

Overall, the 38% lower offending level for individuals in treatment does not seem excessive provided it is clear that this is an effect for this model only, and does not imply that treatment directly causes crime reductions of this magnitude (though it may do). A number of systematic reviews and meta-analyses have explored the possibility of a causal relationship between treatment and lower rates of subsequent offending. Overall the evidence is positive though not conclusive. Prendergast *et al*. (2002) examined 78 studies completed between 1965 and 1996, 46 of which featured randomized study designs. They found that treatment was associated with statistically significant reductions in drug use and crime. A meta-analysis by Mattick *et al* (2009), using only randomised control trials, found only three studies that measured criminal activity. And though it found a risk ratio of 0.39 (which means that the number of individuals that went on to commit crime in the treatment group was only 39% as high as the number of individuals who went on to commit a crime in the control group) this was not statistically significant.

Establishing a trend of OCUs in treatment

To establish a trend in numbers of OCUs in treatment, two primary sources were used. For the years from 2001 to the present, the National Drug Treatment Monitoring System (NDTMS) and its precursors[128] was the main source. For the years 1993 to 2001, the Regional Drug Misuse Databases (RDMD) were used.[129] For the years prior to 1993, the trend was estimated

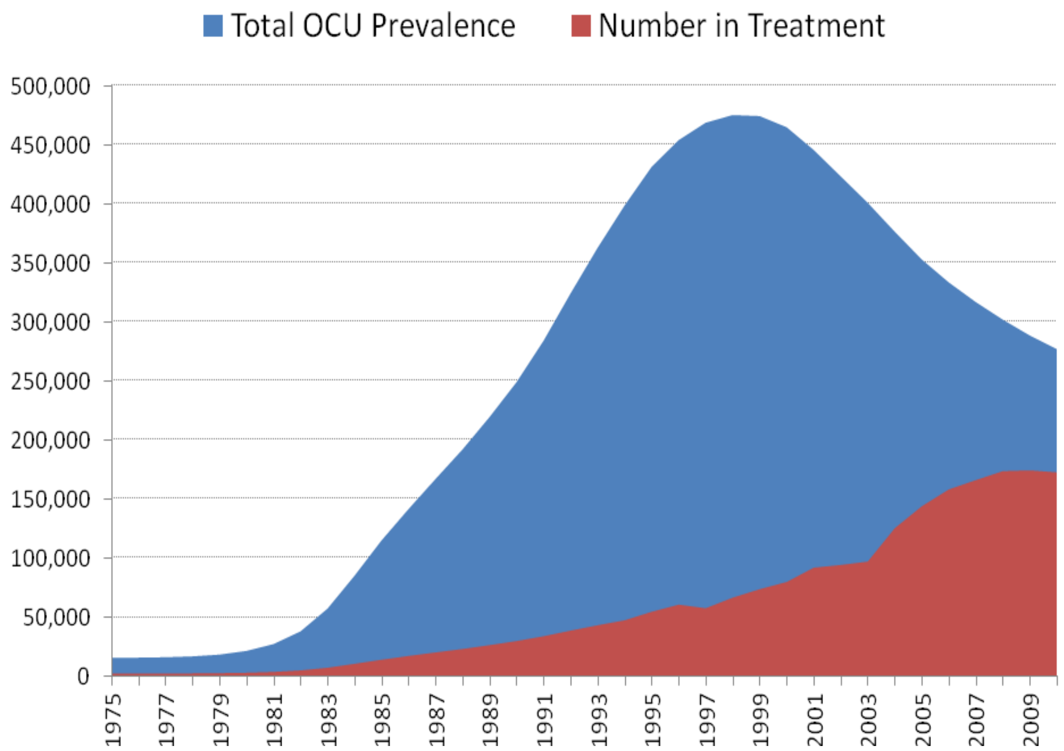
[127] The convictions data also had attrition of a sort given that only 799 of the 1075 individuals in the original sample could be matched (76%), but this was probably because the remaining 24% didn't have a conviction throughout baseline or follow up periods. If these individuals were genuinely not offending this would bias the treatment effect upwards as these individuals would have no change (given that it is impossible to improve on zero offending). However, Gossop et al (2006) report that there were no differences between the matched and the unmatched group in terms of self-reported offending. It seems likely then that this group were simply better at avoiding detection and that their exclusion is not biasing the results.

[128] This involved converting financial year results to calendar years by, for example, creating a value for 2010 by adding 75% of the 2010/11 value to 25% of the 2009/10 value.

[129] The NDTMS has published numbers for OCUs in treatment for each year. The RDMD data works on six-monthly counts of new treatment presentations which will obviously under-count the total population in contact with treatment but may also contain some double-counting if individuals present in consecutive six-month periods. Fortunately there is some overlap between the two sources, so for the period from 1998-2001 values are available for both the NDTMS precursor (see http://www.medicine.manchester.ac.uk/healthmethodology/research/ndec/factsandfigures/NDTMSstatistics/NDTMSAnnualReport0405.pdf) and the RDMD, which allows us to establish a relationship between the two. We found that adding the two six-month counts on the RDMDs typically gave a value that was 68% of the NDTMS in-contact figure. This allowed us to project OCU in-treatment figures back to 1993.

using available evidence.[130] The results of this process are summarised in Figure 68.

Figure 68: Modelled OCU population showing proportion estimated to be in treatment



Sources: NDTMS, RDMD

<u>Establishing offending rates for OCUs who get arrested in a given year and those who do not</u>

For the arrestee method, two studies were located that could be used to estimate arrestee-OCU offending rates. These were the Arrestee Survey and the New-Adam study. For those OCUs not arrested in a given year, the Offending, Crime and Justice Survey (OCJS) was used.

On its own, the OCJS, if extrapolated to the entire OCU population, would be likely to underestimate the proportion of acquisitive crime committed by OCUs, due to the absence of the most problematic drug users, who are unlikely to be involved in a household survey. But equally, extrapolating from the arrestee studies to the entire OCU population would give an over-estimate

[130] It was assumed that the estimated proportion of OCUs in treatment in 1993 (about 10%) held all the way back to 1975. This is a crude estimate, but is unlikely to affect the results of the model hugely given that generally evidence would suggest that the percentage of users in effective treatment during this period was quite low.

of offending because not all OCUs get arrested in any given year,[131] hence the approach taken here of combining the two.[132][133]

Again, full details of these studies are to be found in Appendix 6, which also includes a description of how OCUs were identified on these surveys and how offending volumes were converted into average annual offending rates per OCU, as shown in Table 28 below.

Table 28: Average annual offending rates from arrestee studies, OCJS, all crimes

Average number of self-reported crimes per OCU per year					
Arrestee Survey		**New-Adam**		**OCJS**	
Domestic burglary	1.38	Domestic burglary	6.82	Domestic burglary	0.00
Commercial Burglary	2.59	Commercial burglary	10.02	Commercial burglary	0.00
Theft of vehicle	1.57	Theft of vehicle	15.54	Theft of vehicle	1.01
Theft from vehicle	3.49	Theft from vehicle	13.01	Theft from vehicle	0.03
Theft from person	1.49	Theft from person	1.90	Theft from person	0.00
Commercial robbery	0.42	Robbery	4.09	Commercial robbery	0.00
Personal robbery	0.42	Fraud	14.88	Personal robbery	0.00
Other theft	25.50	Handling	34.08	Other theft	1.19
Violence	1.30	Dealing	17.25	Violence	1.77
Criminal damage	7.91	Shoplifting	41.14	Criminal damage	0.00
Shoplifting	223.21			Shoplifting	0.54
				Drug supply	4.73
Total	**269.29**	**Total**	**158.73**	**Total**	**9.26**

[131] Adults arrested in the previous year were removed from the OCJS dataset in order to ensure that there was no overlap between the two surveys, as this could lead to double-counting.
[132] This approach is identical to that taken in Home Office Research Report 73 and further details on the methodology for combining the data from the two surveys can be found in that publication.
[133] A limitation of the approach is that, while adult arrestees were covered in the Arrestee Survey, data on juvenile arrestees were only available from the OCJS. Juvenile arrestees may not be well represented in the OCJS due to the fact that household surveys are unlikely to include those prolific offenders and/or frequent drug users with chaotic lifestyles. Also, using these surveys introduces the possibility that offending drug users who have not been arrested may be under-represented. The Arrestee Survey will not include offending drug-users who have not been arrested and this group may be unlikely to respond to a household survey such as the OCJS. However, using three years' worth of Arrestee Survey data (rather than a single year) helps to minimise this possibility by extending the period in which offenders might be arrested.

As with the treatment studies, the totals should not be directly compared across studies as each survey asked about different types of crime. But clearly, the offending rate suggested by the OCJS is far lower than for the other two. This is partly a reflection of the fact that all OCUs who had an arrest in the year of the survey were removed from this cohort because our aim in using that survey was to generate an offending rate for OCUs who are not captured by the Arrestee Survey. In that light it is less surprising that the self-reported offending rates are much lower.

Using the figures in Table 28, a subset of comparable CSEW acquisitive crime types was established, by removing commercial crimes and combining relevant categories together. The results are shown in the table below:

Table 29: Average annual offending rates from arrestee studies, OCJS, all CSEW crimes

Average number of self-reported crimes per OCU per year (CSEW acquisitive crime only)					
Arrestee Survey		**New-Adam**		**OCJS**	
Domestic burglary	1.38	Domestic burglary	6.82	Domestic burglary	0.00
Theft of vehicle	1.57	Theft of vehicle	15.54	Theft of vehicle	1.01
Theft from vehicle	3.49	Theft from vehicle	13.01	Theft from vehicle	0.03
Theft from person	1.49	Theft from person	1.90	Theft from person	0.00
Personal robbery	0.42	Robbery (minus commercial robbery)	3.68	Personal robbery	0.00
Other theft	25.50			Other theft	1.19
Total	**33.86**	**Total**	**40.95**	**Total**	**2.23**

As with the treatment studies, there is a reasonably high degree of agreement between the two arrestee estimates: 40.95 CSEW acquisitive crimes per year from NEW-ADAM and 33.86 from the Arrestee Survey. However, given that the former makes a large assumption around extrapolating from a binary offending measure (see Appendix 6), the lower Arrestee Survey estimate was used in the final model.

<u>Dividing the OCU population between arrestees (in a given year) and non-arrestees</u>

There is a large difference between the Arrestee Survey and OCJS offending rates in Table 29. The Arrestee Survey figures are based on self-reported offending from regular users of heroin/crack (see Appendix 6 for the exact definition of `regular') who have been arrested in that year. The OCJS rate excludes those who have been arrested. It is therefore important to ensure that the higher rate from the Arrestee Survey is only extrapolated to the proportion of the OCU population who get arrested in any given year.

Scaling up the Arrestee Survey/OCJS populations by the number of adult arrestees in England and Wales during 2004/05 for the Arrestee Survey and 2004 mid-year population estimates for England and Wales for the OCJS gives an estimate for the number of OCUs captured by the surveys (and the proportion arrested). This is shown in Table 30.

Table 30: Number of OCUs captured by Arrestee Survey, OCJS and implied percentage arrested

Definition	OCJS	Arrestee Survey	Total	% Arrested
Use of heroin or crack more than twice a week	38,000	68,000	106,000	64.2%
Use of heroin or crack at least once a week	50,000	77,000	127,000	60.6%
Use of heroin or cocaine more than twice a week	38,000	78,000	116,000	67.2%
Use of heroin or cocaine at least once a week	106,000	100,000	206,000	48.5%

The bottom row suggests that the definitions employed to identify OCUs on the two surveys has failed to identify the entire population, given that the published estimate for OCUs in 2004/05 is 327,466. The `missing' OCUs are likely to be those who use heroin or crack less than once a week. These will be divided between those, irregular users, who get arrested and those who don't, so it is likely that the offending rate of this group would be somewhere between the rates implied by the Arrestee Survey and OCJS respectively. However, to be conservative, the OCJS rate was used for this population in the model.

Finally it is necessary to assume that the proportion of those *arrested* OCUs, who use heroin/crack at least once per week is the same throughout the entire period 1975-2015 as it was in 2003-06 when captured during the Arrestee Survey (i.e. just under a third: 100,000/327,466 = 30.5%). In practice this means that the higher Arrestee Survey offending rate was applied to less than a third of total OCUs for each year of the modelled OCU trend. The remainder were assumed to be offending at the OCJS offending rate. The fact that the rates are very different does match other evidence showing that a minority of OCUs commit the majority of the crime.

Establishing a counterfactual

For both treatment and arrestee approaches it was necessary to establish a credible counterfactual. That is, how much of the crime predicted was caused by opiate/crack use and how much would have been committed anyway? The latter need to be subtracted off as it is only the additional offences that reflect the epidemic's effect on crime trends.

As in other areas, a number of methods for establishing the counterfactual were tried for the purposes of triangulation. Three of these have been explored in an unpublished paper by Bryan *et al* (2013); but a further method was also added. The four methods, which produce reassuringly similar estimates, are outlined below:

1) **Matching**. One method employed by Bryan *et al*, (2013) is to compare the amount of crime committed by OCUs with the amount of crime committed by otherwise similar individuals who do not take drugs. This involves matching two sets of individuals on a variety of factors associated with offending. The most important weakness of this method is that because matching can only be done using observed characteristics, there is a risk of confounding the true causal impact of drug use on crime with the influence of unobservables (such as family history or pre-existing personality traits) which are determinants of both crime and drug use (Bryan *et al*, 2013). In other words, although the two cohorts may look the same, there may be an important underlying factor that causes both crime *and* drug use which will bias the results in favour of ascribing more crime to drug use rather than other factors. Bryan *et al* (2013) attempt to minimise this bias by choosing variables which, as far as possible, reflect fundamental risk factors specific to the individual, and by selecting matching variables which pre-date current drug use. Using this method they find that between 4% and 17% of the acquisitive crime committed by heroin users would have been committed anyway, even if the individuals hadn't started using drugs.

2) **Using arrestee samples**. Bryan *et al* (2013) compare the results from their first approach with another method which assumes that in the absence of drug use, average offending levels for drug-using arrestees would be the same as those of non-drug using arrestees. Using this method, they find that 13% of the acquisitive crime committed by heroin users would have been committed anyway. Again, this ignores the unobservable differences that are likely to drive higher offending among drug-using arrestees. If underlying factors push the most criminally prone individuals into drug use *and* crime then this estimate will be biased downwards.

3) **Self-reported causality**. A final method employed by Bryan *et al* involves using survey questions to ascertain offenders' perceptions of whether drugs were the causal element. For example, the Arrestee Survey contained a question in which drug users were asked whether each crime they committed was performed "in order to obtain money to buy drugs." In this way, crimes that were *not* committed for this reason could be thought of as a counterfactual – i.e. crimes that would have been committed anyway. This produced an estimate that around 25% of acquisitive offences would have occurred anyway (i.e. were not committed to get money for drugs). Whilst intuitively persuasive, this

counterfactual could be biased in either direction. It could be biased downwards if individuals are tempted to ascribe more of their offending to drug use than actually occurred; this may be the case if drug use is seen as a more acceptable excuse than other reasons. But equally it could be biased upwards. This is because additional crime could be caused by drug use in more ways than simply stealing items to buy drugs. For example, drug use is likely to make an individual less employable meaning they may have to steal more essential items like food and clothing.

4) **Within-individual methods**. Arguably the strongest counterfactual methodology is to look at offending changes within the same individual. That is, to look at changes in the offending levels of the same person during periods of addiction and non-addiction. This method has the advantage of not being biased by underlying factors that differ between individuals because it uses the same individual in different time periods. However, only a few studies have looked at the amount of crime committed by OCUs over extended periods of time (including periods of non-use) and all – to our knowledge – are from the US (Nurco *et al*, 1985; Ball *et al*, 1983; Shaffer *et al*, 1984). The Ball *et al*, 1983, study contains enough information to calculate the total amount of crime committed during addiction (80%) and non-addiction periods (20%). In other words, the study would suggest that around 20% of the crime committed by OCUs would probably have occurred anyway, for reasons not connected to heroin/crack.

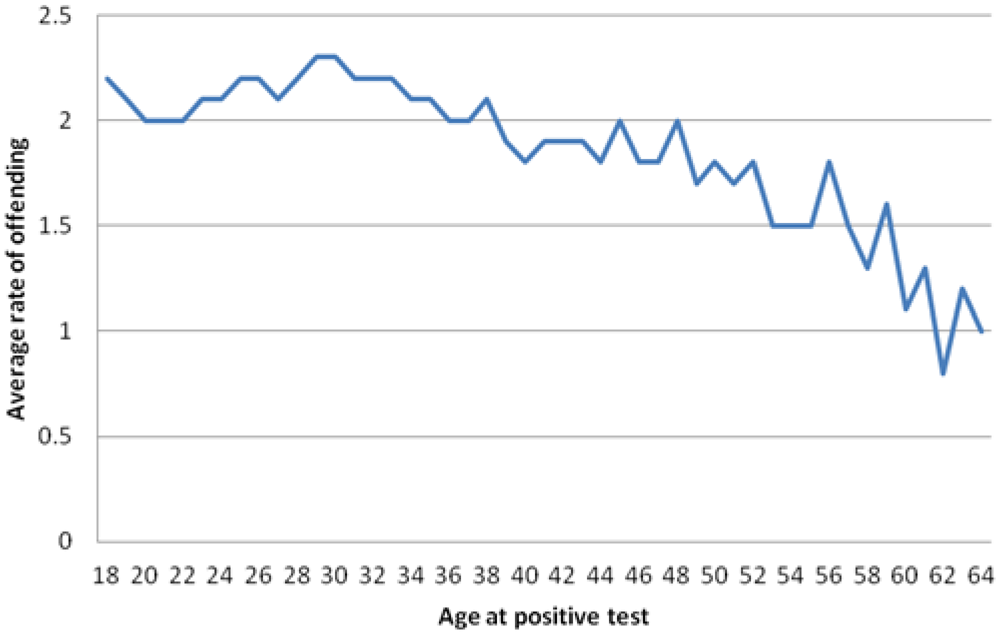
Assimilating the results of the four counterfactual methods, and taking some confidence from the fact that they all produce results in a similar range, it was concluded that there is little evidence for a counterfactual "effect" of more than 25%. In other words, it is unlikely that more than 25% of the acquisitive crime committed by OCUs would have been committed in the absence of the epidemic. Arguably the most robust method (method 4) gives an estimate of 20% and this is used for the main model, but sensitivity analysis was also conducted to see the effects of a 30% and 50% counterfactual i.e. assuming that only 70% and 50% respectively of crimes committed by OCUs are *extra* crimes driven by opiate/crack use.[134]

Finally, a potential criticism of the counterfactual needs to be addressed. It is generated from a US study from more than 30 years ago: Ball et al (1983), which looked at heroin users only. So it is valid to ask whether the results are applicable to a different location (England & Wales), at a different time and to both heroin and crack users. In terms of timings, heroin use in the US was close to its peak in the early 1980s, meaning results from that period are probably more applicable to studying the UK heroin epidemic than results from other years. But, to test this, and the other generalizing assumptions, the results from the Ball et al study were compared with available data from the Drugs Data Warehouse, which captures statistics on the OCU population for

[134] Also note that the current OCU population still has an average age less than 40. Thus both graphs suggest that there is scope for further crime reduction providing there is no new epidemic.

England and Wales in the late 2000s. This revealed a very similar picture, see Figures 69 and 70.

Figure 69: Average proven offending rate for OCUs, by age[135]



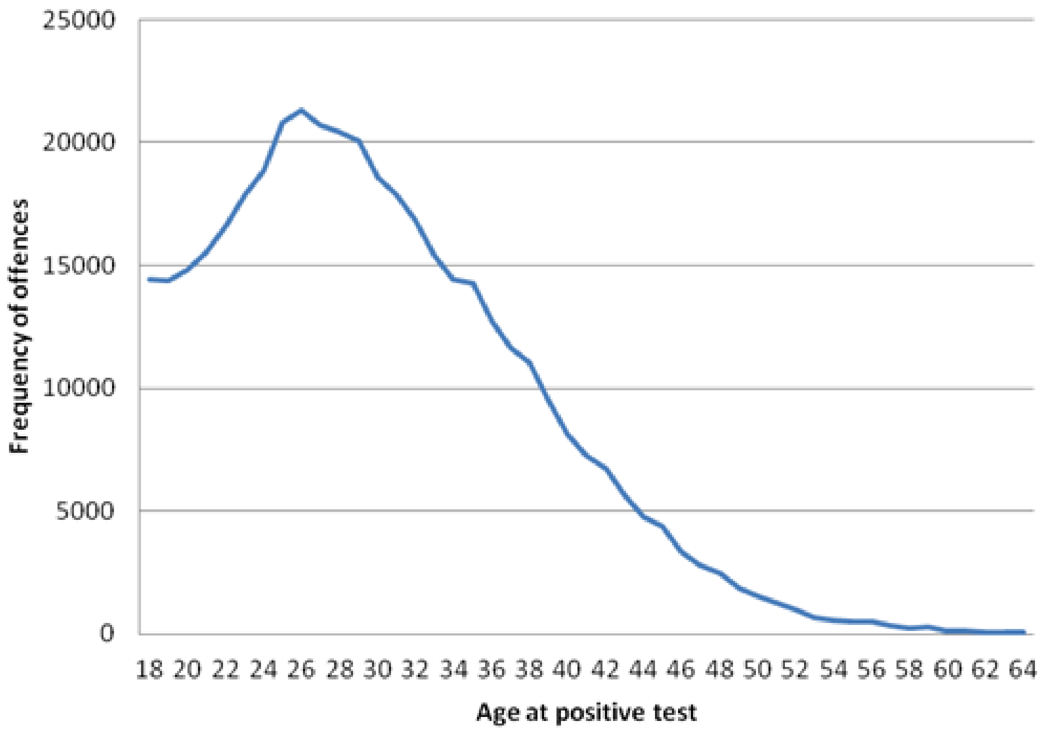
Note: Individuals were classed as OCUs by virtue of the fact that they posted a positive Drugs Intervention Programme test for opiates following an offence during that year.

Source: Drugs Data Warehouse

(Figure 70 on next page.)

[135] The offending rate shown on this chart is considerably lower than that from the self-report studies because it covers proven offending. i.e. it is offences for which an individual receives a caution or conviction. Evidence shows that only a small proportion of offences reported by offenders results in a caution or conviction (Farrington et al, 2006).

Figure 70: Frequency of proven offences committed by OCUs, by age



Note: Individuals were classed as OCUs by virtue of the fact that they posted a positive Drugs Intervention Programme test for opiates during that year.

Source: Drugs Data Warehouse

These charts appear to show two very different criminal career curves neither of which matches up to the typical offending profile that peaks at around 18 and then tails away quickly. The top graph is *not* a representation of the typical age-crime curve of any one individual who becomes addicted to crack/heroin at some point. What it shows is that if an individual is currently regularly using crack/heroin at age 40, their crime *rate* is likely to be much the same as if they were regularly using at age 20. In other words, it matches – for the most part – the Ball *et al* study in showing that until the late 40s, crime levels can stay very high *during periods of addiction*, regardless of age.

However – generally speaking, there are far fewer individuals addicted at age 40 than 20 because i) OCUs tend to die earlier (Hickman *et* al, 2003) ii) some will have successfully quit and iii) even those that haven't completely quit tend to cycle in and out of addiction periods from their late 20s onwards, so at 20 the chances of an OCU being in a non-addiction period are small whereas at 40 they are pretty high. So when these factors are taken into account (by multiplying the rate of offending *when addicted* to the number of individuals who test positive for opiates/crack at each age), this produces the curve in Figure 70, which is a bit more like the standard age-crime curve though with a noticeably later peak.

For the purpose of the counterfactual analysis then, it is clear that the results from the Ball *et al* (1983) analysis are compatible with the OCU population in the UK. But the above graphs also suggest an additional important inference. To the extent that OCU populations today capture individuals who are ex-users in partial recovery, they are likely to have lower offending rates than at the earlier stages in the epidemic. The methods employed in this paper to try and model this are admittedly crude. Hence further data on the different offending rates of the current OCU population would be welcome.[136]

Final Results

The final step was to combine the offending rate estimates with the counterfactual adjustment (i.e. subtracting crimes that would have been committed anyway) and cohort breakdown (so that, for example, the crime estimates for the arrestee cohort are only applied to our best estimate for total arrestee OCUs in any given year). This produced two trends in OCU-generated crime - i.e. crime arising *as a direct result* of these individuals becoming opiate/crack users – one for the treatment method and one for the arrestee method.[137]

For the treatment based approach the calculation was:

$$((Pr^T \times \%Tx^T \times CrTx) + (Pr^T \times (1-\%Tx^T) \times CrNTx)) \times CF$$

Where:

PrT = OCU prevalence in year T

%TxT = Proportion in treatment in year T

CrTx = In-treatment crime rate

CrNTx = Not-in-treatment crime rate

CF = the counterfactual adjustment (0.8).

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[136] Bennett (2000) also conducted a counterfactual analysis of sorts using the NEW ADAM data, see table 7.5 in Bennett (2000) (http://tna.europarchive.org/20100413151441/http://www.homeoffice.gov.uk/rds/pdfs/hors205.pdf). Bennett reasoned that in the absence of drug use it could be argued that OCU arrestees would have the same level of illegal income as non-OCU arrestees. Using this method they calculate that *total* illegal income in the sample would be 52% lower. This is not quite the same as the counterfactual methods examined above. This is effectively a crude estimate of how much lower *total* arrestee crime would be without drug use and hence shouldn't be compared to the counterfactual estimates above, which deal only with offending by OCUs. The 52% estimate therefore is more comparable with the final results of this study which estimate the overall effect on crime trends. In a similar vein, the Bennett et al estimate shows that drug use probably affects total volumes of crimes considerably, with around half of all crime being affected. It is possible to extract a more direct comparison to the counterfactual estimates generated here from the Bennett et al analysis and this reveals that around 28% of the illegal income obtained by OCUs was not the result of drug use, which is similar to the estimates above.

[137] Although the main goal of this exercise is producing an estimate for the average level of criminality per OCU, evidence suggests that this average is only useful in applying to aggregate-level populations. It is not a reasonable estimate for any one OCU. This is because the amount of crime committed by drug users has a very skewed distribution: a few individuals commit a very large amount of crime and the majority commit relatively little or none at all.

For the Arrestee Survey/OCJS approach, the formula was:

$((Pr^T \times \%Arr^T \times CrArr) + (Pr^T \times (1\text{-}\%Arr^T) \times CrNArr)) \times CF$

Where

PrT = OCU prevalence in year T

%ArrT = Proportion of OCUs arrested in year T

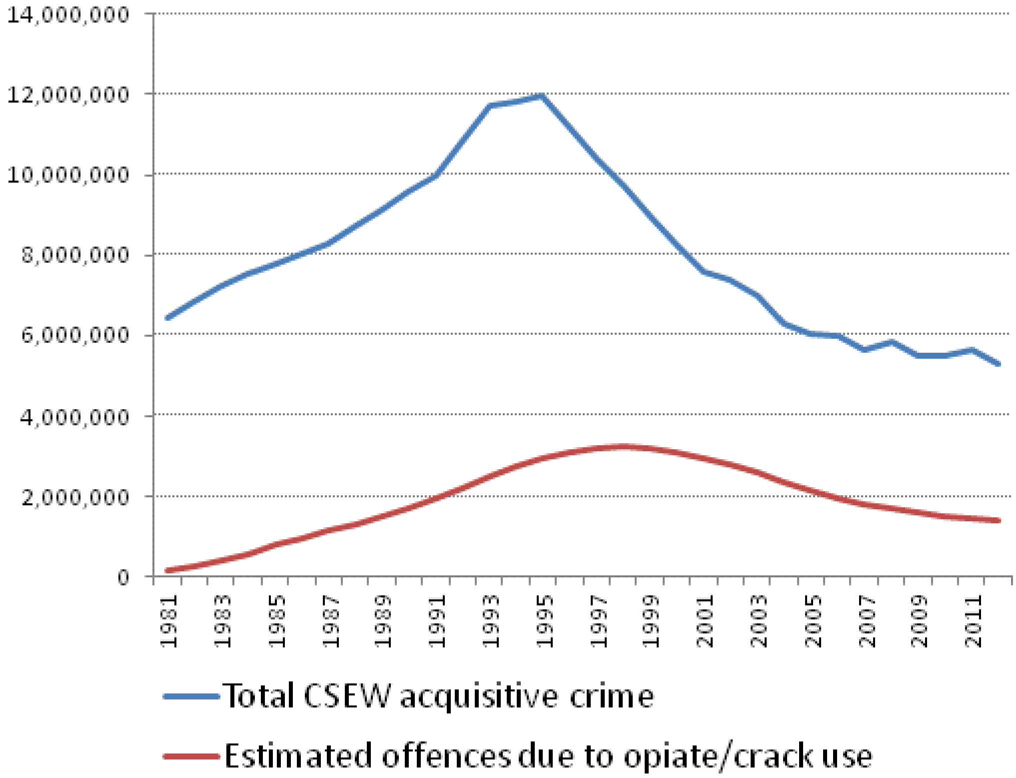
CrArr = OCU Arrestee crime rate

CrNArr = OCU non-arrestee crime rate

CF = the counterfactual adjustment (0.8).

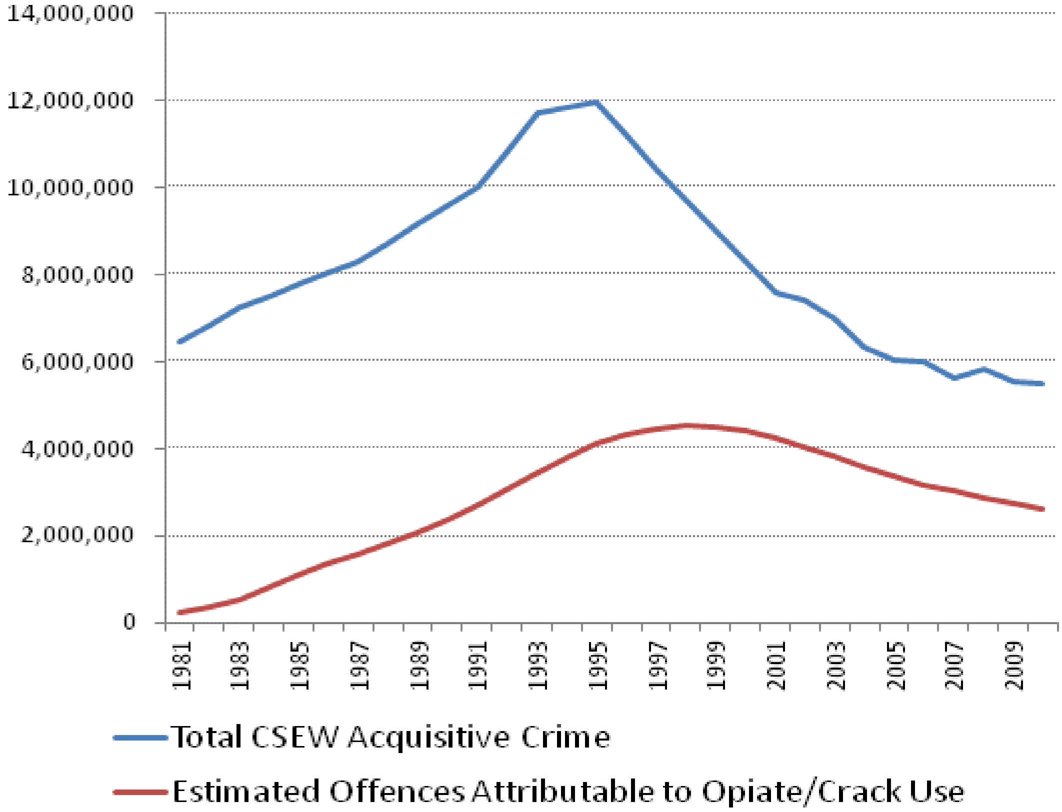
These formulae produce an estimate for the *additional* crime generated by the OCU cohort in every year throughout the series (1975-2015). These are shown by the graphs below:

Figure 71: Total CSEW acquisitive crime and estimated offences generated by opiate/crack use, treatment method



(Note: CSEW values have been converted to calendar year figures.)

Figure 72: Total CSEW acquisitive crime and estimated offences generated by opiate/crack use, arrestee method



(Note: CSEW values have been converted to calendar year figures.)

The estimated impact this had on overall CSEW acquisitive crime trends was then estimated by making the following calculation:

R^{OCU} / R^{TOT} = Percentage of total rise in crime `explained' by opiate/crack use.

F^{OCU} / F^{TOT} = Percentage of total fall in crime `explained' by opiate/crack use.

Where:

R^{OCU} = total rise in additional OCU offences(from 1981 to peak)
R^{TOT} = total rise in CSEW acquisitive crime (from 1981 to peak)
F^{OCU} = total fall in additional OCU offences (from peak to 2012)
F^{TOT} = total fall in CSEW acquisitive crime (from peak to 2012).

This gives the following results:

Table 31: Final modelling results

	Treatment approach	Arrestee Survey/OCJS approach
Estimated percentage of CSEW acquisitive crime rise explained (1981–95)	54.9%	77.0%
Estimated percentage of CSEW acquisitive crime fall explained (1995–2012)	28.9%	32.9%

Notes: OCJS is the Offending, Crime and Justice Survey.
CSEW is the Crime Survey for England and Wales.

The model can also be used to show that even though today's OCU cohort is almost certainly smaller and older than it was at epidemic peak, opiate/crack use may still be responsible for a large number of offences – between 1.4m and 2.4m per year according to our different estimates.[138] The model also reveals that, whichever estimate is used, the decline of the OCU cohort is probably still exerting important downward pressure on CSEW acquisitive, and therefore total crime.

The model estimates only acquisitive crimes captured by the CSEW. The most common OCU crimes are drug dealing and shoplifting, neither of which features.[139] This implies that the impact of the OCU cohort on overall crime is likely to be bigger than these estimates suggest. One way to illustrate this is to examine shoplifting rates from the studies mentioned above in comparison with the fall in shoplifting suggested by the Commercial Victimisation Survey (see Chapter 2). The studies would suggest that, in aggregate, OCUs commit around 60 shoplifting offences per person annually due to opiate/crack use. Multiplying this by our estimate for the decline in OCUs from the peak year (1998) to 2012 would imply a fall of just over 10 million shoplifting offences. This compares well with the actual fall of more than 14 million offences suggested by the CVS between 2002 and 2012.[140]

It is also crucial to note that the model used to generate these estimates employs a number of assumptions and simplifications typical of models of this type. A complete list of these, and the evidence behind them, is contained in Appendix 7. Where possible, the more conservative option was generally taken, but some decisions might still be challenged. So, to check the sensitivity of the final results to these assumptions, sensitivity analysis was conducted. The model was re-run varying some of the central parameters to see how much this changed the final result. The findings are shown below:

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[138] These numbers are calculated simply be multiplying the estimated number of OCUs for the current year (2013) by the estimated offending rates of these populations using the treatment and arrestee methods.

[139] This means that the true number of offences committed by OCUs per year is likely to be far larger than the 1.4m to 2.4m estimated above. A recent National Treatment Agency paper, which included all offence-types rather than just those captured by CSEW, suggested that the true number of offences committed by OCUs per year may be around 15m (NTA, 2012). This is arrived at by taking the mid-point estimate for counterfactual offences from the paper and adjusting down by the number of offences they estimate has been prevented due to treatment.

[140] As the other sections of this paper have made clear – this does not imply that every OCU commits 60 shoplifting offences each year. Rather, it suggests that a few OCUs commit far more than this and most commit far less. But for aggregate calculations, the average is accurate to use. Also note that the counterfactual and extrapolation adjustments were made in this shoplifting calculation, which is why this figure is smaller than the 80 offences per year average for the NTORS cohort.

Table 32: Sensitivity analysis

Proportion of the Rise in Acquisitive Crime Explained				
	Treatment Method		***Arrestee Method***	
Sensitivity	Result	Difference from central estimate (in percentage points)	Result	Difference from central estimate (in percentage points)
Central Estimate	54.9%	0.0%	77.0%	0.0%
Number of new OCUs per year in 1975, pre-epidemic = 3000 (Central = 2000)	51.9%	-3.0%	72.8%	-4.2%
Number of new OCUs per year in 1975, pre-epidemic = 1000 (Central = 2000)	55.0%	0.1%	77.2%	0.2%
OCU prevalence in recent years increased by 10% (from Hay et al estimates used in central).	58.9%	4.0%	82.4%	5.4%
OCU prevalence in recent years decreased by 30% (from Hay et al estimates used in central).	73.1%	18.2%	101.2%	24.2%
OCU prevalence in recent years increased by 10% (from Hay et al estimates used in central).	50.1%	-4.8%	70.4%	-6.6%
OCU prevalence in recent years decreased by 30% (from Hay et al estimates used in central).	35.9%	-19.0%	51.4%	-25.6%
All offending rates increased by 30%.	71.4%	16.5%	100.1%	23.1%
All offending rate increased by 10%	60.4%	5.5%	84.7%	7.7%
All offending rates decreased by 30%	38.4%	-16.5%	53.9%	-23.1%
All offending rates decreased by 10%	49.4%	-5.5%	69.3%	-7.7%
Proportion of OCUs arrested annually = 40% (Central = 30% from Arrestee Survey)	54.9%	0.0%	96.3%	19.3%
Proportion of OCUs arrested = 20% (Central = 30% from Arrestee Survey)	54.9%	0.0%	55.4%	-21.6%
Counterfactual (proportion of OCU offending that would have occured anyway) = 30% (Central = 20%)	48.0%	-6.9%	67.3%	-9.7%
Counterfactual = 50% (Central = 20%)	34.3%	-20.6%	48.1%	-28.9%
Fixed 5% Annual Exit Rate (Central uses a varying rate based on the Hser study)	22.0%	-32.9%	31.9%	-45.1%
5% Exit Rate / 50% counterfactual / Offending Rate decreased by 30%	15.4%	-39.5%	22.3%	-54.7%

Proportion of the fall in acquisitive crime explained				
	Treatment method		***Arrestee method***	
Sensitivity	Result	Difference from central estimate (in percentage points)	Result	Difference from central estimate (in percentage points)
Central Estimate	28.9%	0.0%	32.9%	0.0%
Number of new OCUs per year in 1975, pre-epidemic = 3000 (Central = 2000)	28.8%	-0.1%	32.6%	-0.3%
Incidence in 1975 increased by 1000 to 1000	28.7%	-0.2%	32.6%	-0.3%
OCU prevalence in recent years increased by 10% (from Hay *et al* estimates used in central).	30.7%	1.8%	35.3%	2.4%
OCU prevalence in recent years decreased by 30% (from Hay *et al* estimates used in central).	35.8%	6.9%	42.0%	9.1%
OCU prevalence in recent years increased by 10% (from Hay *et al* estimates used in central).	27.5%	-1.4%	30.9%	-2.0%
OCU prevalence in recent years decreased by 30% (from Hay *et al* estimates used in central).	21.7%	-7.2%	23.1%	-9.8%
All offending rates increased by 30%.	37.6%	8.7%	42.8%	9.9%
All offending rate increased by 10%	31.8%	2.9%	36.2%	3.3%
All offending rates decreased by 30%	20.3%	-8.6%	23.0%	-9.9%
All offending rates decreased by 10%	26.0%	-2.9%	29.6%	-3.3%
Proportion of OCUs arrested annually = 40% (Central = 30% from Arrestee Survey)	28.9%	0.0%	41.2%	8.3%
Proportion of OCUs arrested = 20% (Central = 30% from Arrestee Survey)	28.9%	0.0%	23.7%	-9.2%
Counterfactual (proportion of OCU offending that would have occurred anyway) = 30% (Central = 20%)	25.3%	-3.6%	28.8%	-4.1%
Counterfactual = 50% (Central = 20%)	18.1%	-10.8%	20.6%	-12.3%
Fixed 5% Annual Exit Rate (Central uses a varying rate based on the Hser study)	10.5%	-18.4%	10.8%	-22.1%
5% Exit Rate / 50% counterfactual / Offending Rate decreased by 30%	7.3%	-21.6%	7.6%	-25.3%

The tables demonstrate that the final results are reasonably robust to changes in many of the main parameters. For the rise in acquisitive crime, the counterfactual, the cessation rate and the percentage of OCUs who get arrested display reasonably high levels of sensitivity. But the pre-epidemic rate of OCU incidence, up to 10% changes to the offending rates and the Hay *et al* OCU estimates have far smaller effects. Even in the `ultra-conservative' option at the bottom (in which three parameters are changed), opiate/crack use is responsible for 15-20% of the rise in acquisitive crime. For the acquisitive crime fall, increasing the counterfactual to 50% (i.e. assuming half of offending reported by OCUs would have happened irrespective of drug use) and a change in the cessation rate were the only changes that moved the results more than ten percentage points away from the central estimates.

There are limitations to these analyses of course. Apart from in a very crude way with the `ultra-conservative' option, the degree to which uncertainties might compound each other is not really tested. Plus, there are other aspects of the model (like the application of offending rates to different periods of time) that are uncertain, yet cannot be tested with sensitivity analysis in this way. This is why the modelling results should be seen as exploratory. It should also be noted that no attempt was made to model the potential interactions outlined in the rest of this paper. This again may be a fruitful area for further research.

With these caveats noted, two tentative conclusions were drawn. Firstly, it seems likely that opiate/crack use played a role in both the rise and fall in acquisitive crime in England and Wales over the recent period, though it probably had a bigger overall impact on the rise than the fall. Secondly, there is a chance it was a very significant factor, perhaps even driving more than half of the rise and between a quarter and a third of the fall.

Conclusion

The rise and fall in crime that has occurred in England and Wales and in a number of other developed nations has been the subject of much academic debate. Ultimately though, despite much "imaginative scholarship," a convincing overall explanation remains elusive (Farrell *et al*, 2011).

This paper has attempted to add to the evidence by piecing together the available data and research on the extent to which opiate/crack use may have played a role, both in the sharp 1990s crime peak(s) and the downward trend since, which started steeply and has become more gradual.

Overall, the evidence presented shows that cohorts of opiate/crack users – on aggregate – commit markedly more crime than offenders not taking these drugs (Bennett *et al*, 2008). Studies also agree that the number of users increased dramatically in England and Wales and in many other Western nations and then tailed off as users quit or died (Pearson, 1987; Barrio *et al*, 2013). Those two – largely undisputed - facts offer a compelling explanation for at least some of the rise and fall in crime, which has received relatively little attention, especially in relation to crime's decline.

Probably the main reason why the waning of these opiate/crack epidemics has not always featured prominently in crime-drop research is that two other facts *are* disputed: whether opiates/crack caused the crime committed by OCUs and whether the peaks in drug use correlated with peaks in crime. Lack of high-quality data means these two questions may never be answered definitively.

On causality, the evidence gathered here shows that opiate/crack use almost certainly generated additional offences, but quantifying the precise amount remains challenging. The problem is that evidence also suggests other factors, related perhaps to genetics and upbringing, produced an increased propensity for crime *and* opiate/crack use in many individuals. A key conclusion of this paper is that belief in the importance of such an underlying "third factor" is compatible with the notion that the heroin epidemic was a crucial driver of crime trends. Without the epidemic, underlying propensity for illicit drug use would not have been translated into the *accelerated* and *extended* offending self-reported by some OCUs in repeated studies.

The possibility of a causal relationship is further bolstered by the evidence presented here on the correlation between peaks in opiate/crack use and peaks in crime. A key element of this analysis involved deconstructing local, national and international crime trends to show that there was no single rise and fall. At the national level, England and Wales, the US, Ireland and many Eastern European nations had peaks in acquisitive crime that matched the timing of their heroin epidemics, rather than each other. The same is true for regional exceptions like Merseyside and Edinburgh. No doubt there are areas that do not follow this pattern (and this paper highlighted at least one: West Midlands). But whether or not researchers decide that the geographical crime variation is driven by variation in opiate/crack use, the variation itself should be embraced. Its analysis surely offers the best chance of unlocking the crime-drop puzzle.

This paper focused on England and Wales. It attempted to tell the full story of the epidemic and to tentatively try and quantify its impact on acquisitive crime. For the latter, two models were used. Though both should be viewed as exploratory due to data limitations, they do produce similar results.

Regression analysis, looking at the correlation between OCU indicators and recorded crime trends from 1981-96, found that around 40% of the rise in key crime types like theft and vehicle crime may be attributable to the epidemic.

A second exploratory model that combined our best estimates of OCU numbers through time, with our best estimates for their offending, suggested that opiate/crack use might have driven around half the rise in acquisitive crime in England and Wales and between a quarter and a third of the fall.

These results hide considerable uncertainty. Perhaps the best summary of this paper is that it has demonstrated the existence of an epidemic `narrative', which fits many of the facts currently available, and which suggests opiate/crack use has been an important driver of crime trends. But it has not proven that this is the only explanation for those facts.

That `narrative' would run something like this:

- Following the opening of a new heroin supply route in the late 1970s, England and Wales had a significant drugs epidemic, or wave of epidemics, through the 1980s and early 1990s. This produced a cohort of heroin users, many of whom also used crack as their career developed.

- The cohort was not homogenous. Many (perhaps most) did not become either long-term addicted or prolific criminals and some were offenders before using opiates or crack. While many probably had the clustering of crime risk factors that could have marked them out for a criminal career in the absence of the epidemic, the cohort probably also included a number of individuals whose only crime risk factor was a susceptibility to peer influence at a time when heroin use was spreading in their area. For the first group, heroin use may have accelerated and extended an existing criminal career and for some of the second group heroin may have kick-started a criminal career.

- Crimes committed were mainly minor theft offences. As a result, this cohort became prominent in the offending population and probably had a large impact on total crime, which is dominated by acquisitive crime.

- The crime rise was steady during the 1980s, when the majority of England and Wales remained relatively unaffected by the epidemic. It then increased very rapidly in the 1990s as every police force area except Merseyside reached its peak of opiate/crack use.

- Once the epidemic had spread across England and Wales and all susceptible individuals had been `exposed', the number of new users probably decreased just as quickly as it had risen. Crime therefore began to fall; quickly at first as the less-recalcitrant users quit in significant numbers. But then more steadily as the population whittled down to more established users.

There are several important caveats to this story that need mentioning. Firstly, the effect of the OCU cohort was almost certainly greater on crime *volumes* than on the overall *harm* from crime, because OCUs tend to commit minor theft or drug dealing offences rather than the violent and sexual crimes that cause most harm. As such, it is also important to note that the evidence presented does not explain why violence rose and fell with a similar trend.

The most important caveat though, is that this narrative does not imply that opiate/crack use was the sole factor driving crime trends. This paper has argued instead that trends are never likely to be driven by a single factor. Many factors are likely to have been important and interactions may also be crucial. Indeed, some findings suggest that rapid rises in unemployment, *at a time when heroin use was spreading,* may have exacerbated the crime impact beyond the level that either factor would have had on its own.

The analysis has several policy implications.

It suggests that relative to other drugs, opiate/crack users continue to have the biggest impact on acquisitive crime trends. The central model estimates imply that the number of users will continue to reduce, but at a relatively gradual pace. If the rate of cessation could be increased, the potential for further crime reduction is large.

Raising the cessation rate of the existing cohort is unlikely to be easy though. It is made up largely of older users, many of whom will have repeatedly tried and failed to achieve cessation through existing treatment practices.

Focusing resources on the most important individuals may be the key. Evidence shows that not all opiate/crack users are alike. A minority commit the vast majority of offences. So identifying these individuals is paramount.

The other main policy conclusion is that preventing a future epidemic is crucial. Evidence shows epidemics do not strike all areas simultaneously and there is a lag between epidemic start and the moment it becomes visible on treatment or criminal justice datasets. Local-level monitoring is therefore crucial, so that future epidemics can be restricted before spreading.

Evidence also shows that the main mechanism for epidemic spread is via person-to-person contact, which may have important implications for the way in which, for example, OCU prisoners are housed in relation to non-OCU prisoners. There is also some evidence that supply surges can act as triggers for epidemics, so the prevention of these remains important.

Finally, data in this area is sparse (but improving) and there may be better ways than those employed in this paper to explore the question of whether opiate/crack use is an important driver of crime trends. Suggestions for improving or refining this work are therefore welcomed.

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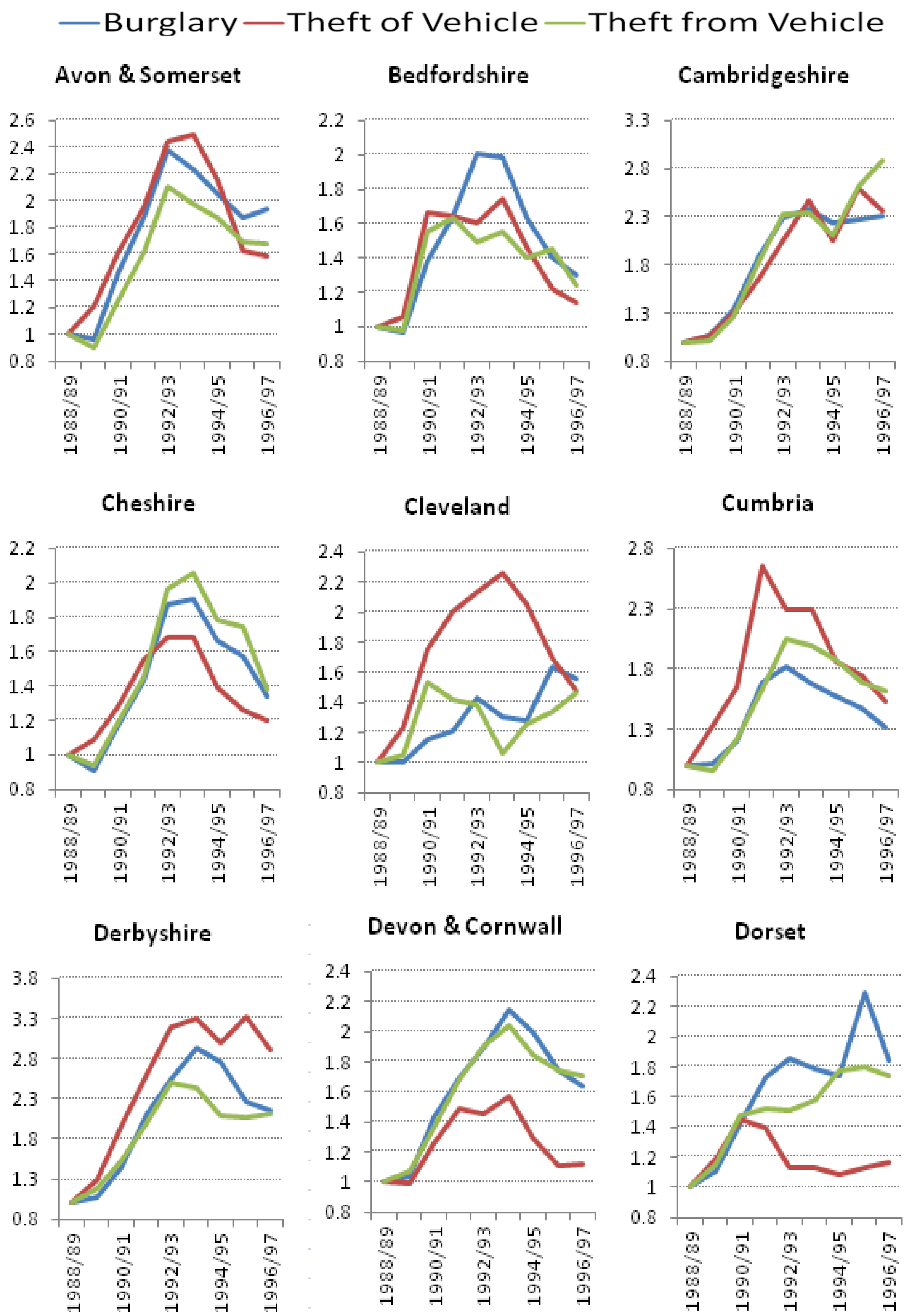
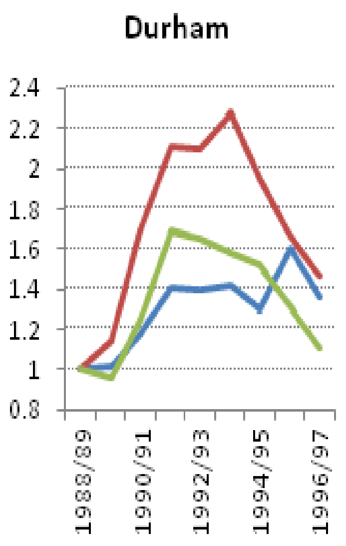
Appendix 1: Table showing peaks in crime types, heroin use and unemployment, by police force area

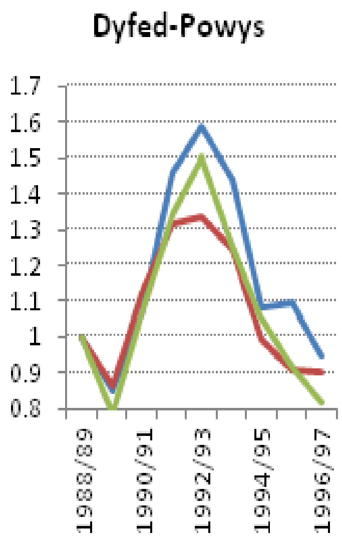
PEAK YEAR								
Police Force Area	**Burglary**	**Theft of Vehicle**	**Theft from Vehicle**	**Un-employment**	**All addicts**	**New Addicts**	**All Heroin Users**	**New Heroin Users**
Avon and Somerset	1992/93	1993/94	1992/93	1993/94	1996	1996	1996	1996
Bedfordshire	1992/93	1993/94	1991/92	1993/94	1995	1996	1996	1996
Cambridgeshire	1993/94	1995/96	1996/97	1990/91	1996	1996	1996	1996
Cheshire	1993/94	1992/93	1993/94	1983/84	1996	1996	1994	1996
Cleveland	1995/96	1993/94	1990/91	1984/85	1996	1996	1996	1996
Cumbria	1992/93	1991/92	1992/93	1993/94	1996	1994	1988	1994
Derbyshire	1993/94	1995/96	1992/93	1986/87	1996	1996	1996	1996
Devon and Cornwall	1993/94	1993/94	1993/94	1993/94	1996	1996	1996	1996
Dorset	1995/96	1990/91	1995/96	1993/94	1996	1996	1996	1996
Durham	1995/96	1993/94	1991/92	1985/86	1996	1996	1996	1996
Dyfed-Powys	1992/93	1992/93	1992/93	1985/86	1996	1992	1992	1992
Essex	1993/94	1992/93	1991/92	1993/94	1996	1995	1996	1995
Gloucestershire	1993/94	1993/94	1993/94	1993/94	1996	1995	1996	1995
Greater Manchester	1992/93	1992/93	1991/92	1985/86	1996	1996	1996	1996
Gwent	1997/98	1993/94	1991/92	1986/87	1996	1996	1996	1996
Hampshire	1992/93	1991/92	1992/93	1993/94	1994	1992	1996	1996
Hertfordshire	1993/94	1992/93	1995/96	1993/94	1996	1996	1995	1996
Humberside	1993/94	1994/95	1993/94	1993/94	1996	1996	1996	1996
Kent	1995/96	1992/93	1993/94	1993/94	1996	1996	1996	1996
Lancashire	1996/97	1993/94	1993/94	1985/86	1996	1996	1996	1996
Leicestershire	1994/95	1993/94	1992/93	1993/94	1996	1996	1996	1996
Lincolnshire	1993/94	1993/94	1992/93	1986/87	1996	1996	1996	1996
Merseyside	1986/87	1987/88	1987/88	1985/86	1992	1990	1991	1990
Metropolitan	1992/93	1982/83	1992/93	1993/94	1996	1996	1996	1996
Norfolk	1993/94	1991/92	1992/93	1993/94	1996	1996	1996	1996
North Wales	1992/93	1992/93	1993/94	1985/86	1996	1996	1996	1996
North Yorkshire	1994/95	1995/96	1994/95	1986/87	1996	1996	1996	1996
Northamptonshire	1993/94	1993/94	1991/92	1993/94	1996	1996	1996	1996
Northumbria	1991/92	1991/92	1990/91	1986/87	1996	1996	1996	1996
Nottinghamshire	1993/94	1991/92	1991/92	1993/94	1996	1996	1996	1996
South Wales	1992/93	1994/95	1991/92	1985/86	1996	1996	1996	1996
South Yorkshire	1993/94	1993/94	1993/94	1986/87	1996	1996	1996	1996
Staffordshire	1993/94	1992/93	1993/94	1983/84	1996	1996	1996	1996
Suffolk	1993/94	1991/92	1992/93	1993/94	1996	1995	1996	1996
Surrey	1993/94	1992/93	1992/93	1993/94	1996	1996	1996	1996
Sussex	1992/93	1991/92	1992/93	1993/94	1996	1996	1996	1996
Thames Valley	1993/94	1993/94	1993/94	1993/94	1996	1996	1996	1996
Warwickshire	1992/93	1993/94	1992/93	1983/84	1996	1996	1996	1996
West Mercia	1993/94	1993/94	1996/97	1985/86	1996	1996	1996	1996
West Midlands	1992/93	1996/97	1987/88	1983/84	1996	1996	1996	1996
West Yorkshire	1993/94	1991/92	1991/92	1985/86	1996	1996	1996	1996
Wiltshire	1992/93	1991/92	1993/94	1993/94	1996	1996	1996	1996

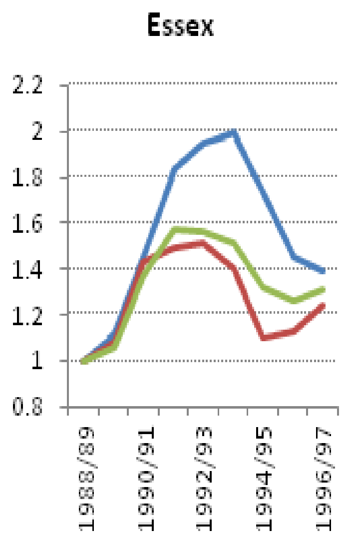
Appendix 2: Trends in acquisitive crime through the crime turning point, by police force area

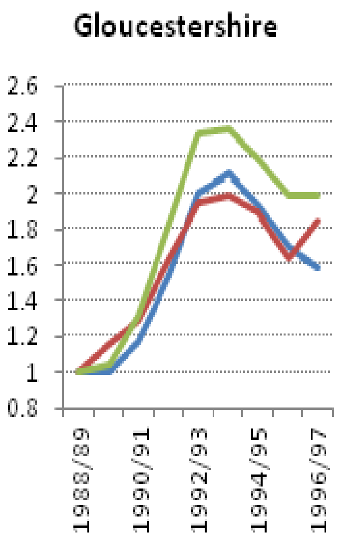
This section shows acquisitive crime trends by force area. The first set of charts has trends indexed to 1989/90 for comparability with Figure 7 in the short version of the paper:

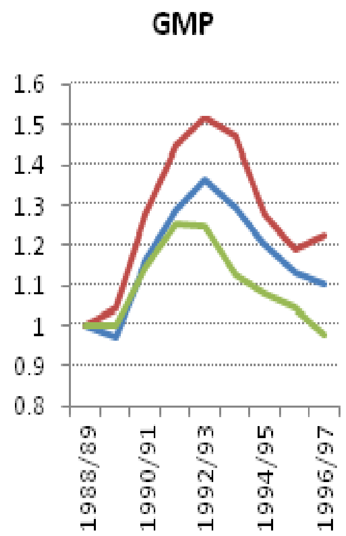


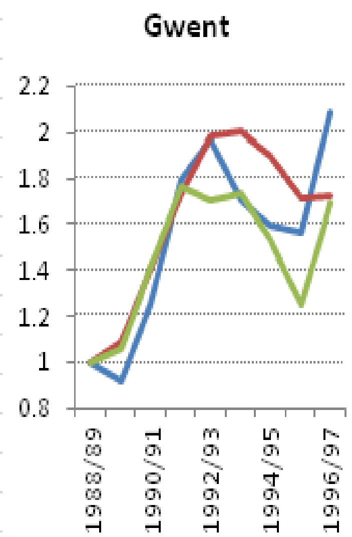

Durham
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

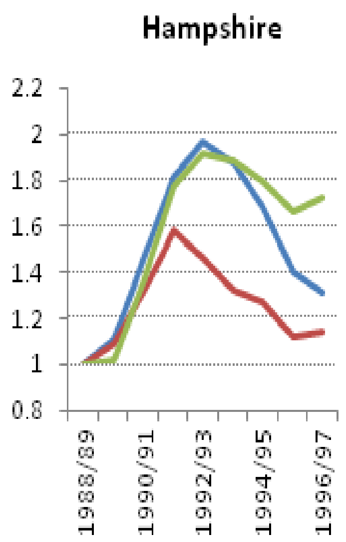

Dyfed-Powys
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

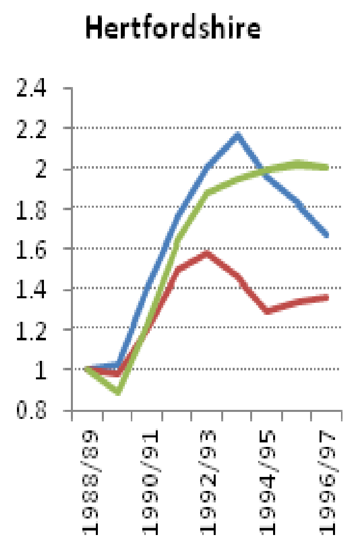

Essex
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

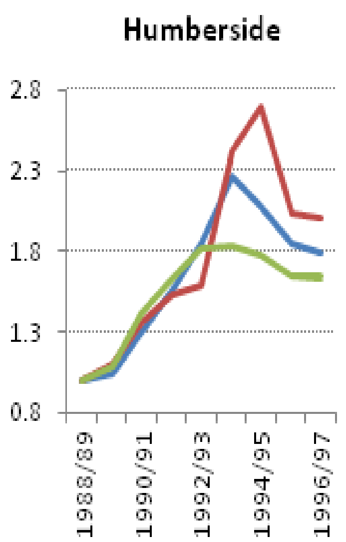

Gloucestershire
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

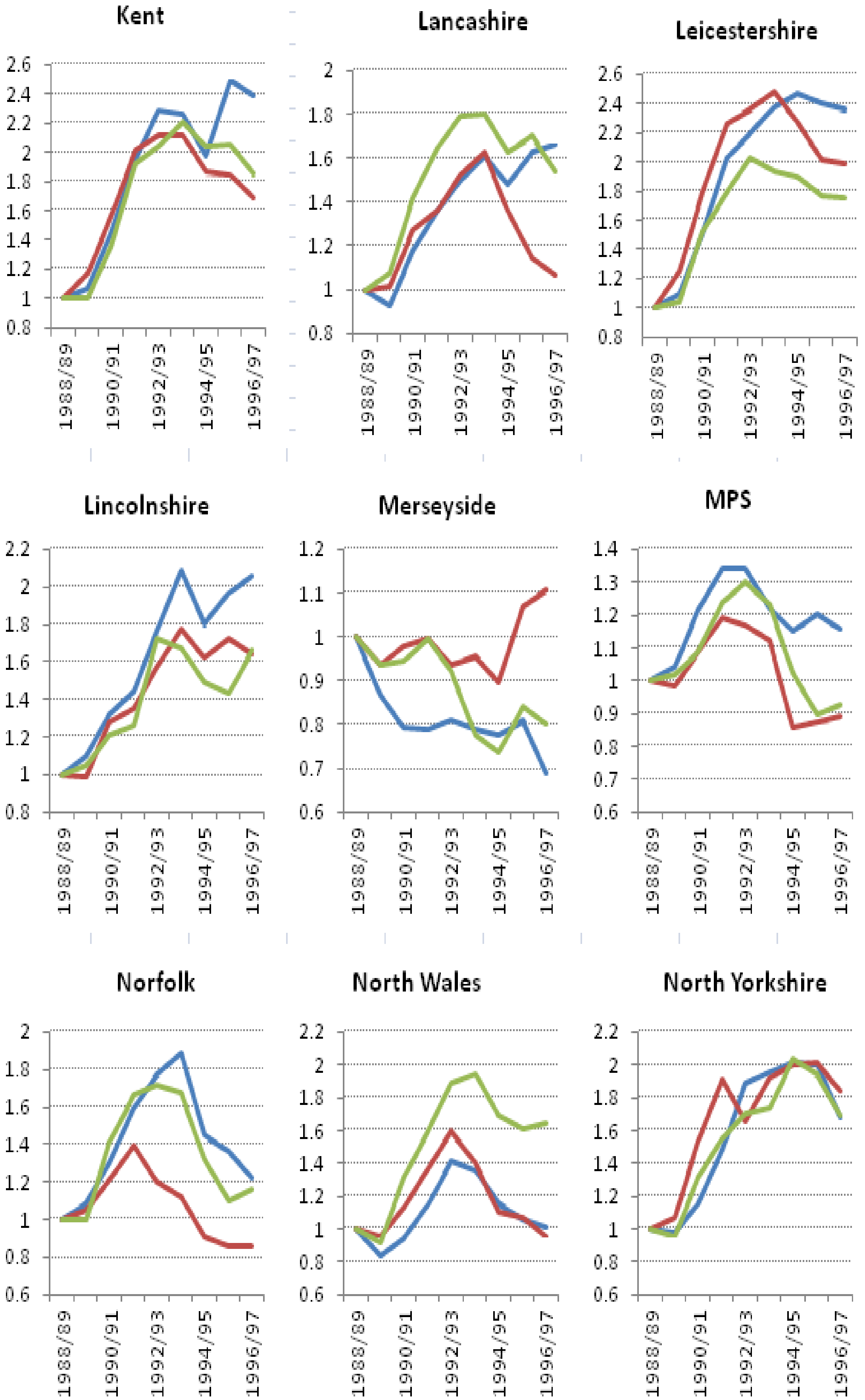

GMP
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

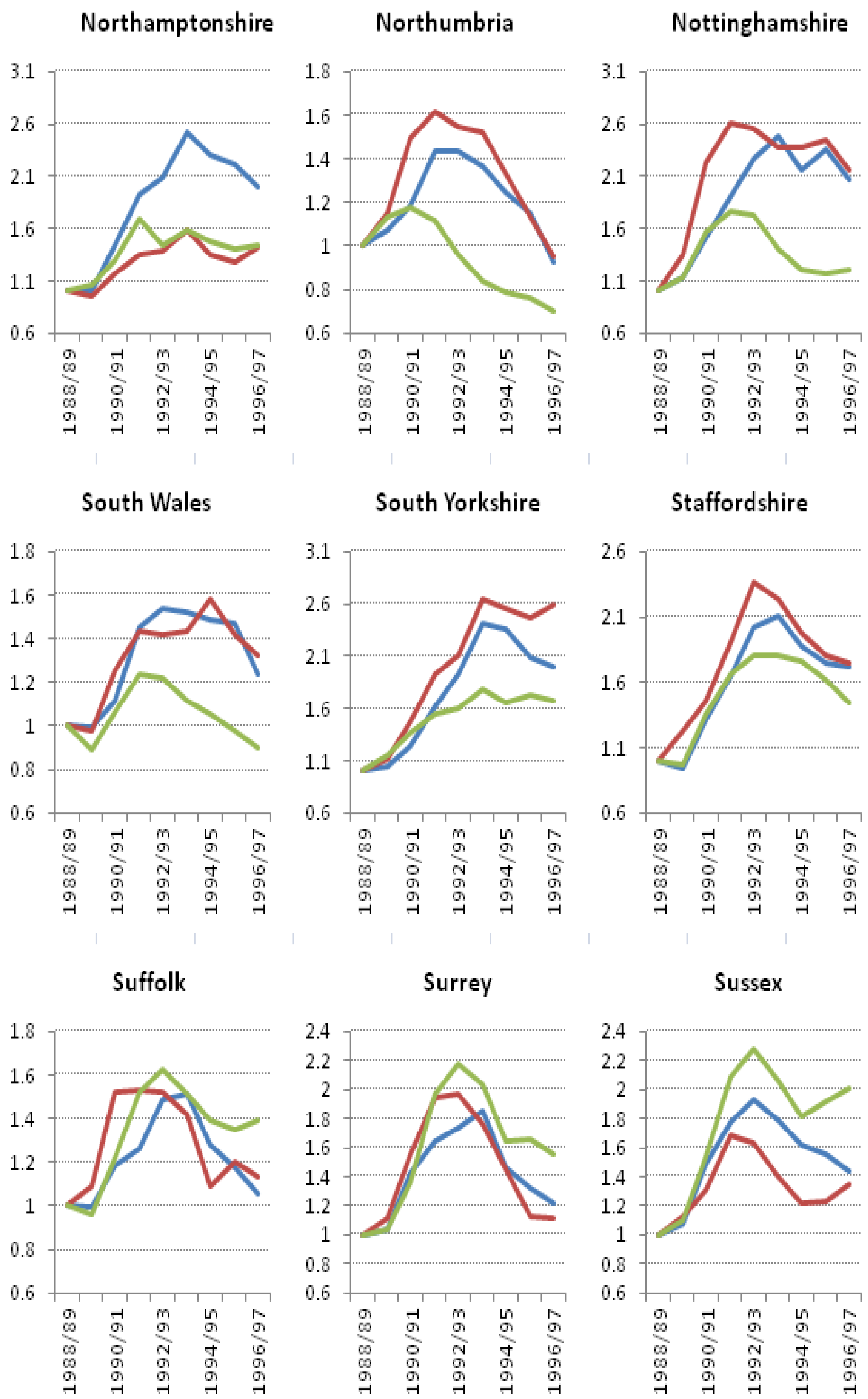

Gwent
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

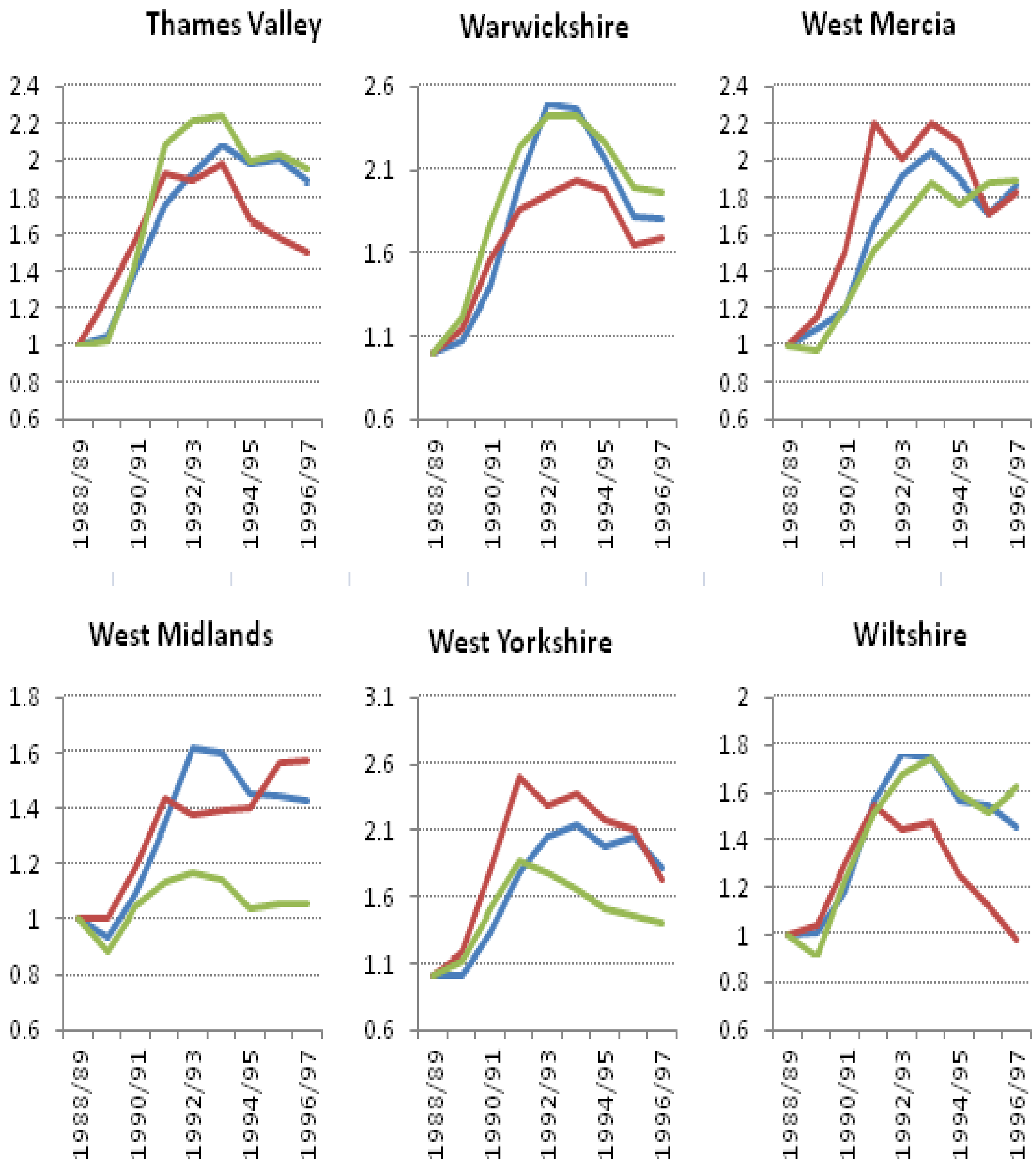

Hampshire
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97


Hertfordshire
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97

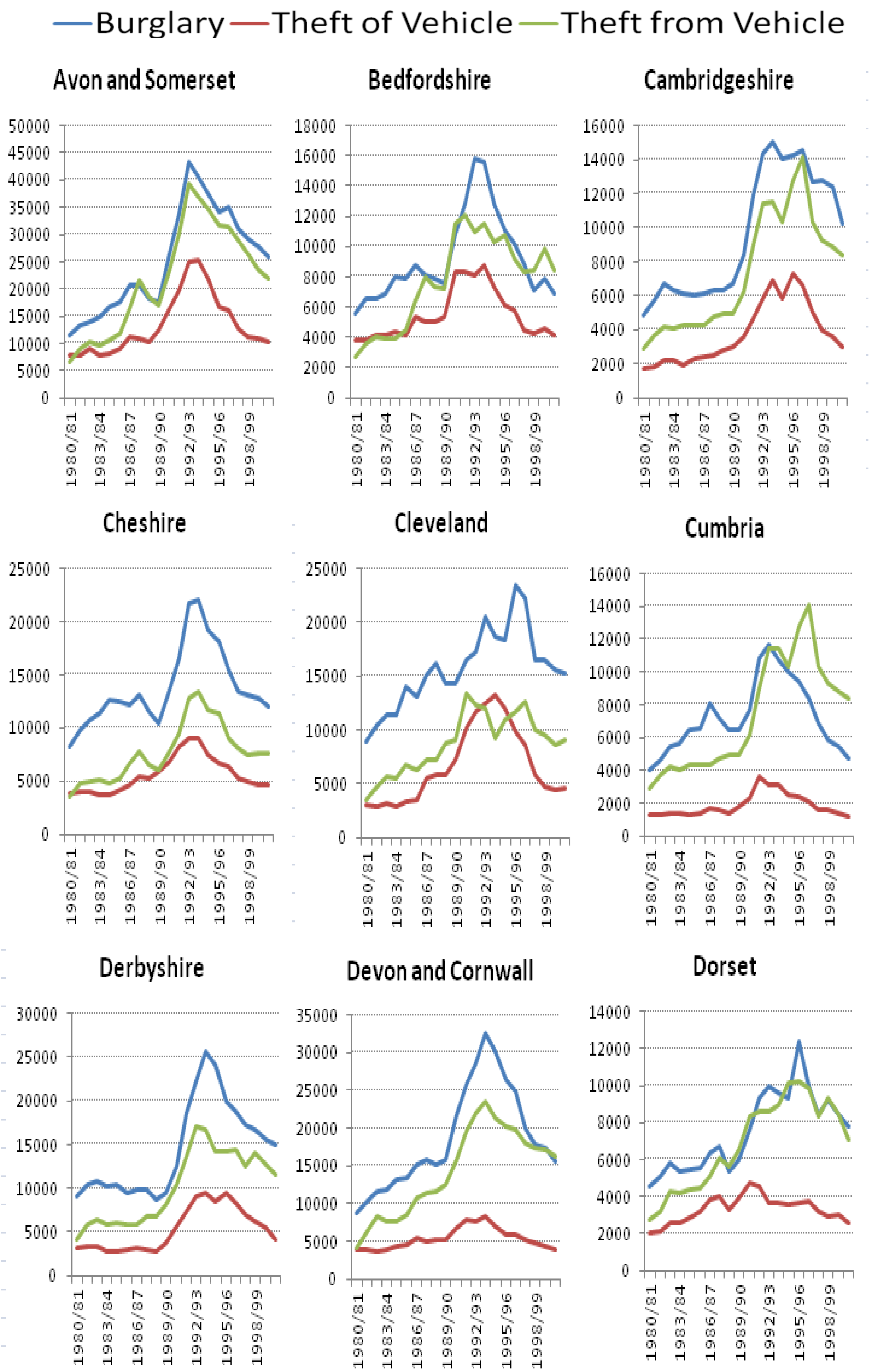

Humberside
2.8
2.3
1.8
1.3
0.8
1988/89
1990/91
1992/93
1994/95
1996/97


Kent
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97
Lancashire
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97
Leicestershire
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97
Lincolnshire
2.2
2
1.8
1.6
1.4
1.2
1
0.8
1988/89
1990/91
1992/93
1994/95
1996/97
Merseyside
1.2
1.1
1
0.9
0.8
0.7
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
MPS
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
Norfolk
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
North Wales
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
North Yorkshire
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97

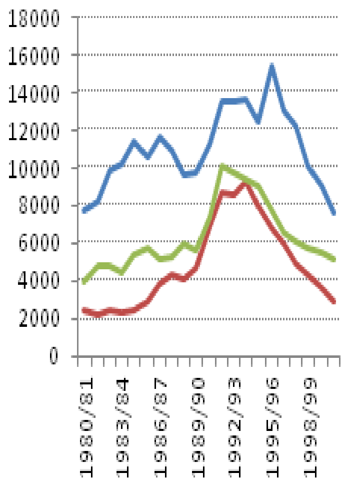

Northamptonshire
Northumbria
Nottinghamshire
South Wales
South Yorkshire
Staffordshire
Suffolk
Surrey
Sussex
1988/89
1990/91
1992/93
1994/95
1996/97


Thames Valley
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
Warwickshire
2.6
2.1
1.6
1.1
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
West Mercia
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
West Midlands
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
West Yorkshire
3.1
2.6
2.1
1.6
1.1
0.6
1988/89
1990/91
1992/93
1994/95
1996/97
Wiltshire
2
1.8
1.6
1.4
1.2
1
0.8
0.6
1988/89
1990/91
1992/93
1994/95
1996/97

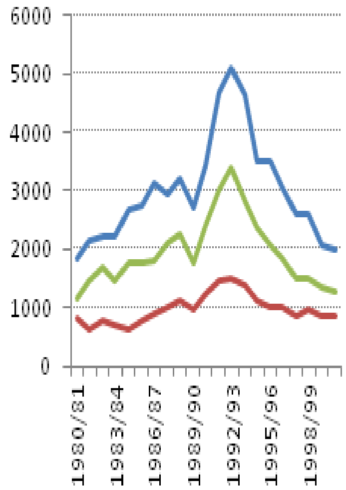
The second set of charts is not indexed. They show crime volumes for the three acquisitive crimes for all police force areas from 1980/81 to 2000/01.



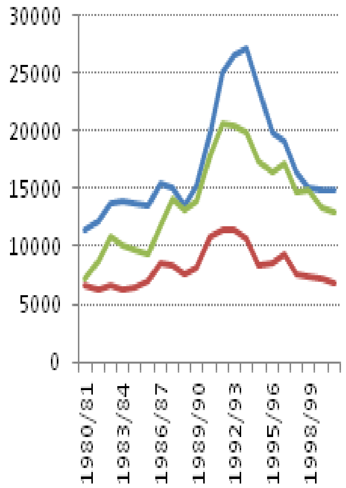
Durham



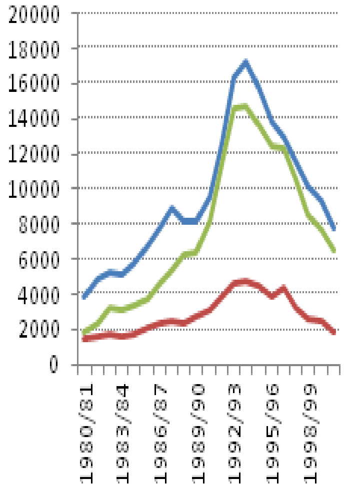
Dyfed-Powys



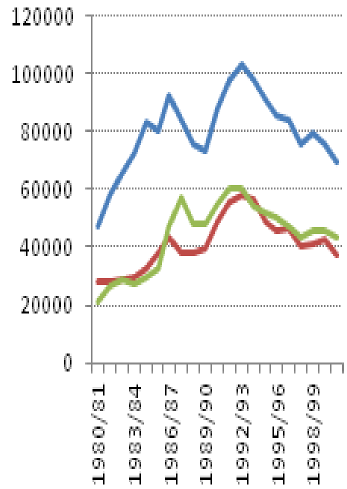
Essex



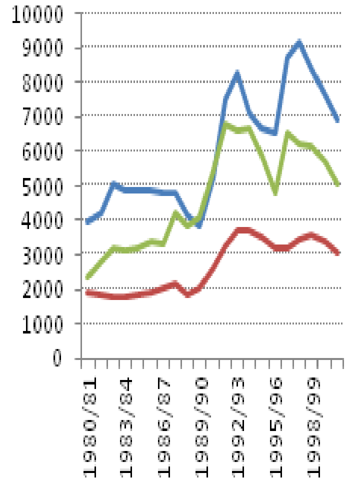
Gloucestershire



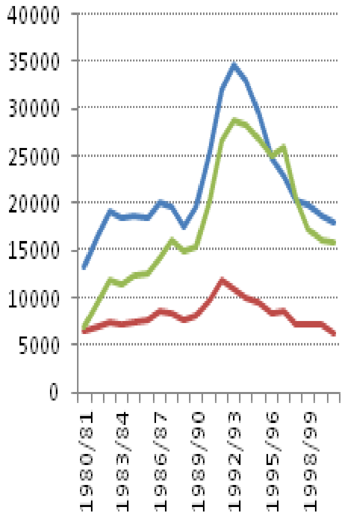
GMP



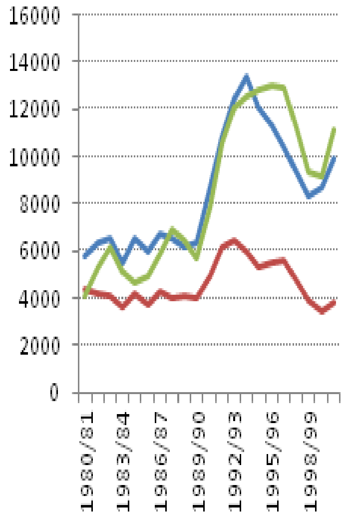
Gwent



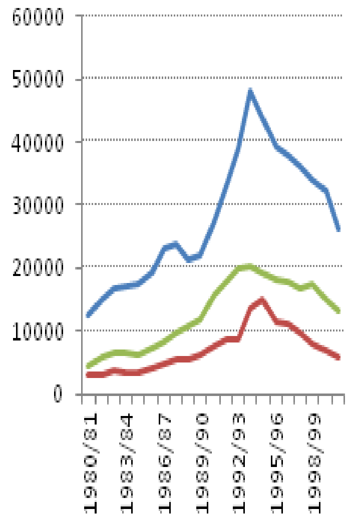
Hampshire

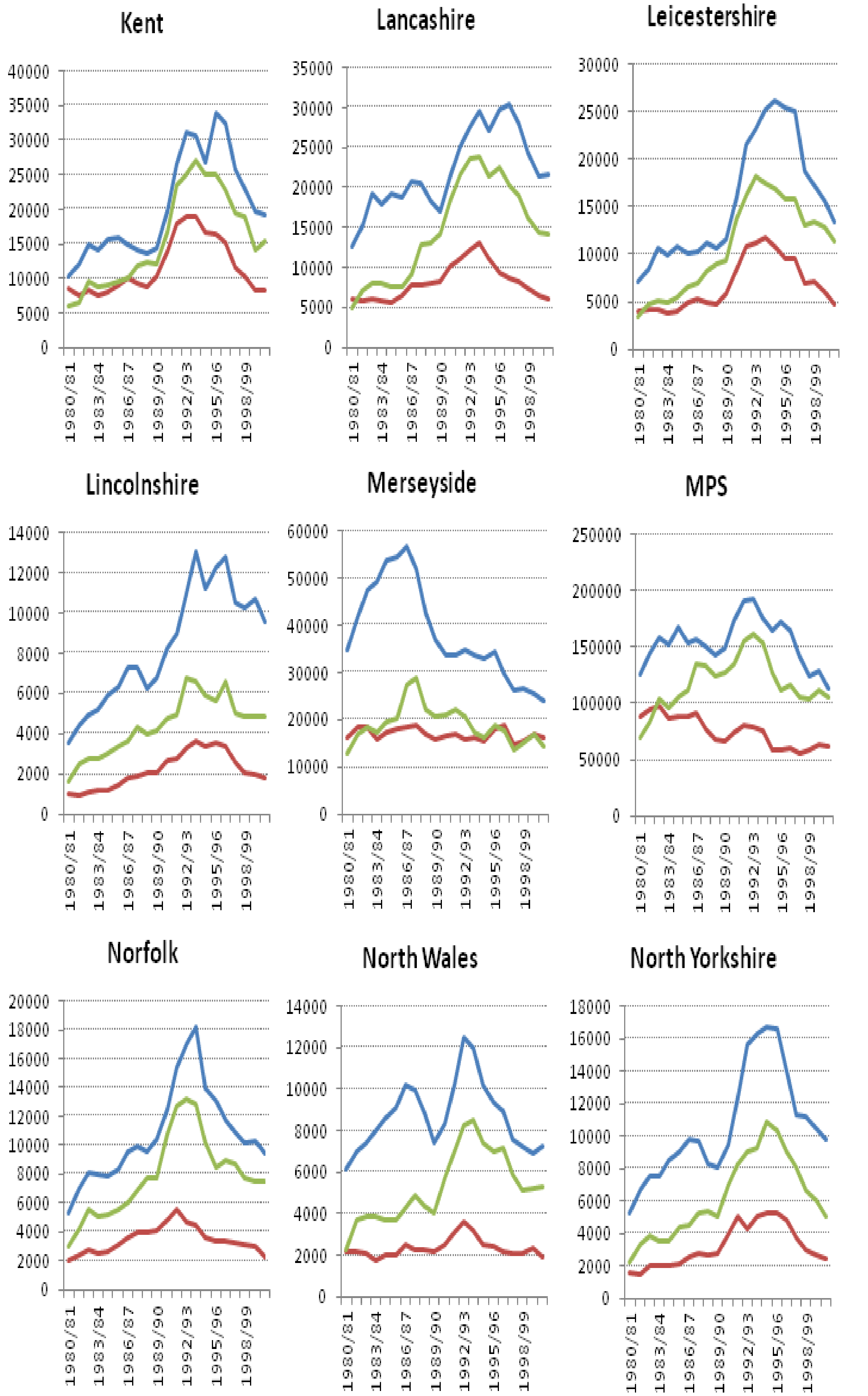


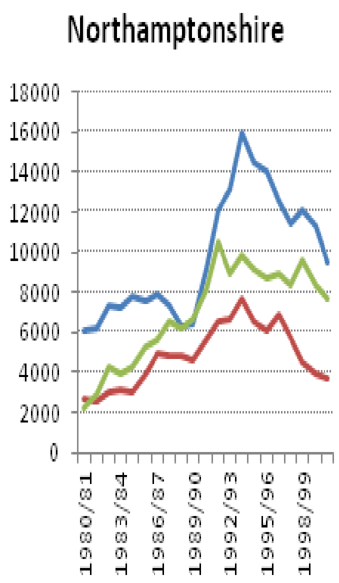
Hertfordshire

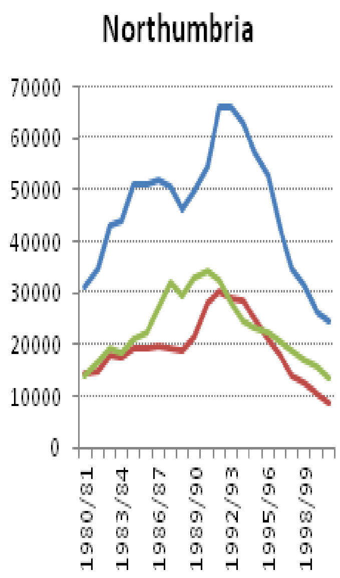


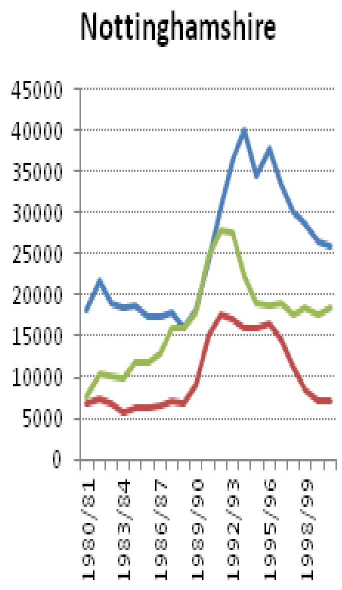
Humberside

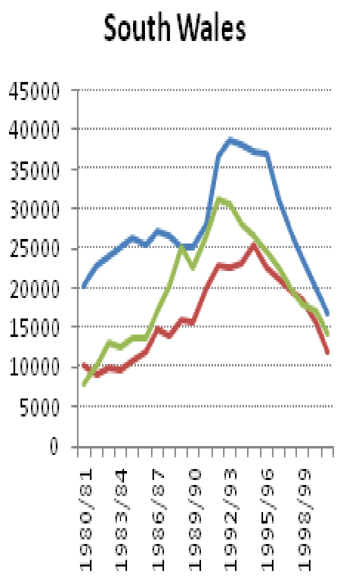


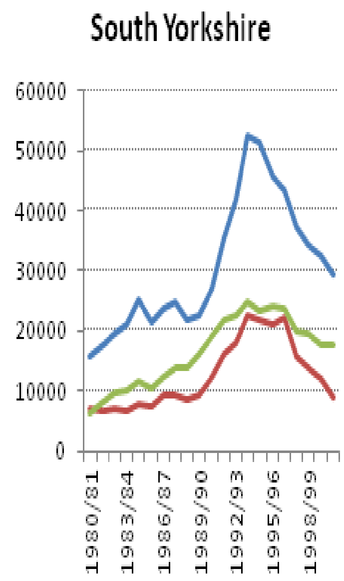

Kent
40000
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
Lancashire
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
Leicestershire
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
Lincolnshire
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
Merseyside
60000
50000
40000
30000
20000
10000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
MPS
250000
200000
150000
100000
50000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
Norfolk
20000
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
North Wales
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99
North Yorkshire
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

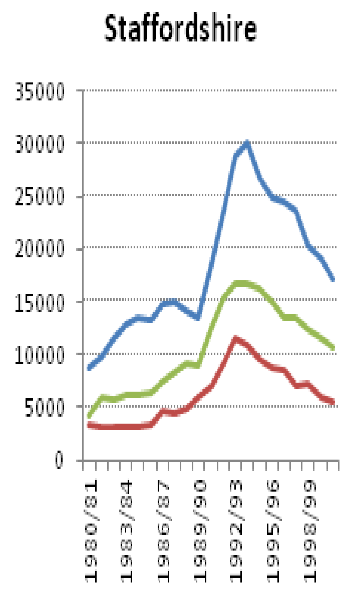

Northamptonshire
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

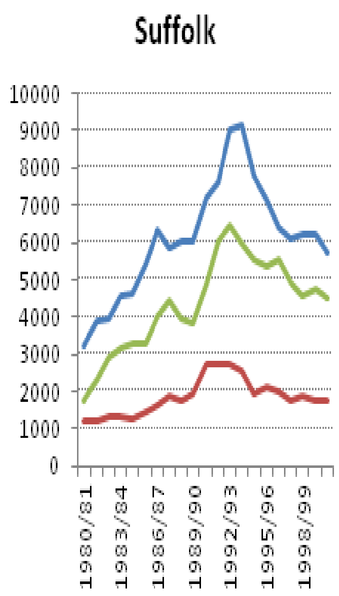

Northumbria
70000
60000
50000
40000
30000
20000
10000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

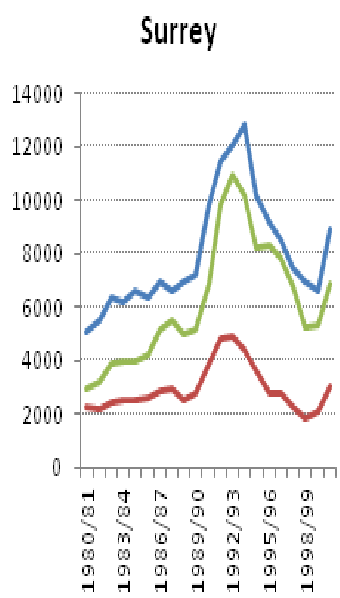

Nottinghamshire
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

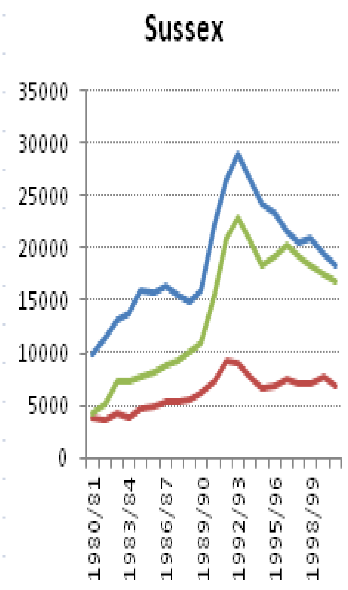

South Wales
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

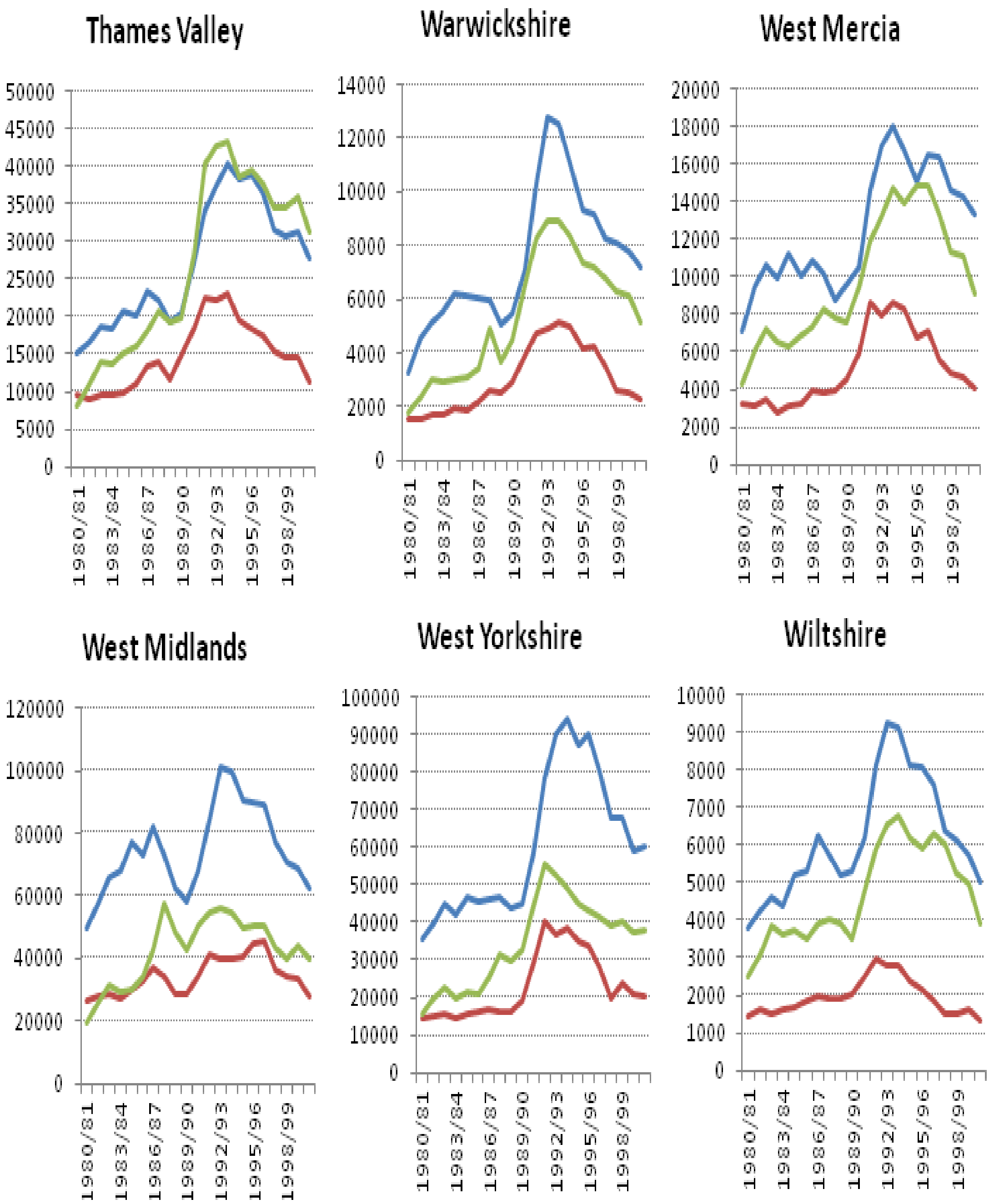

South Yorkshire
60000
50000
40000
30000
20000
10000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99


Staffordshire
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

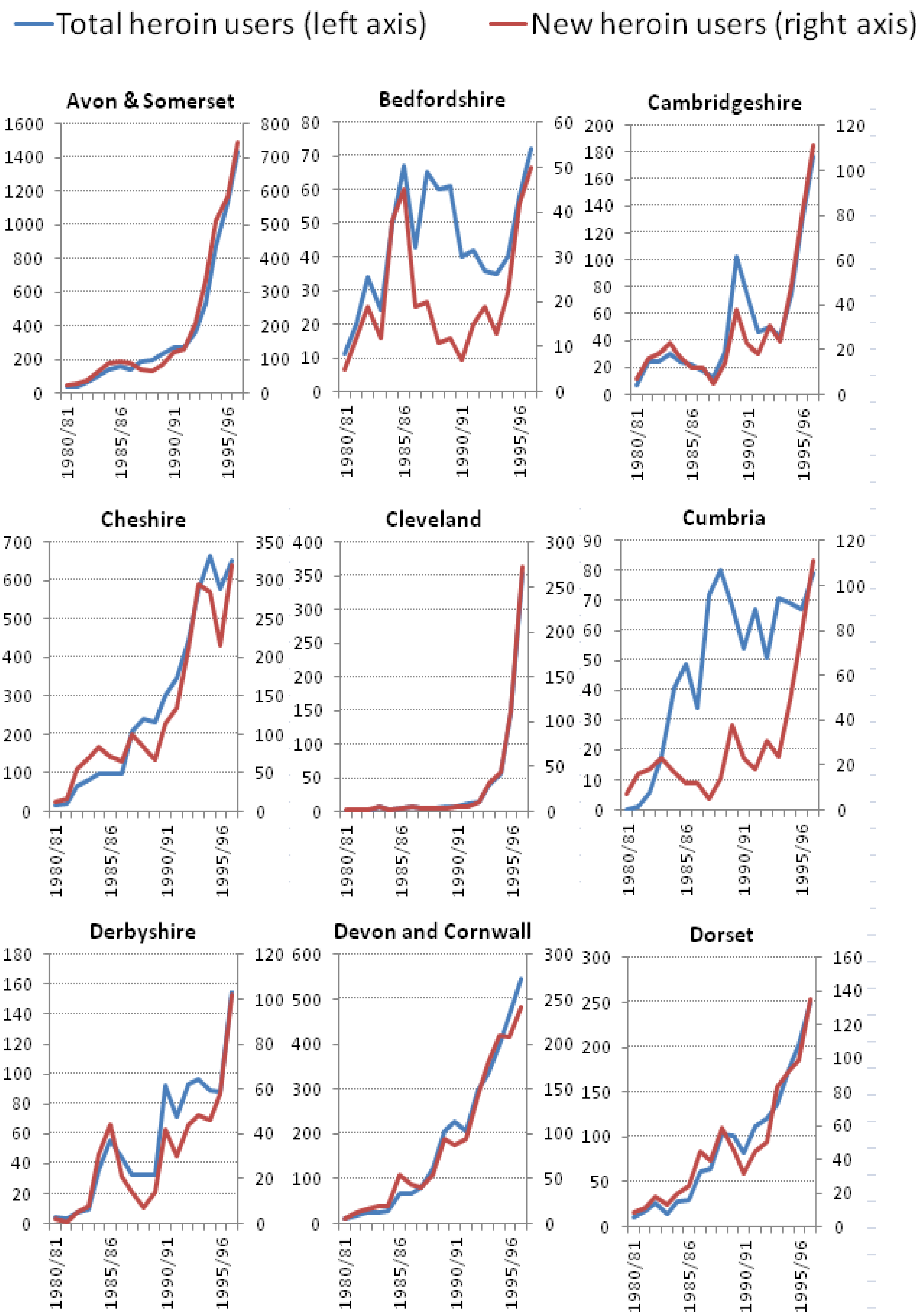

Suffolk
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

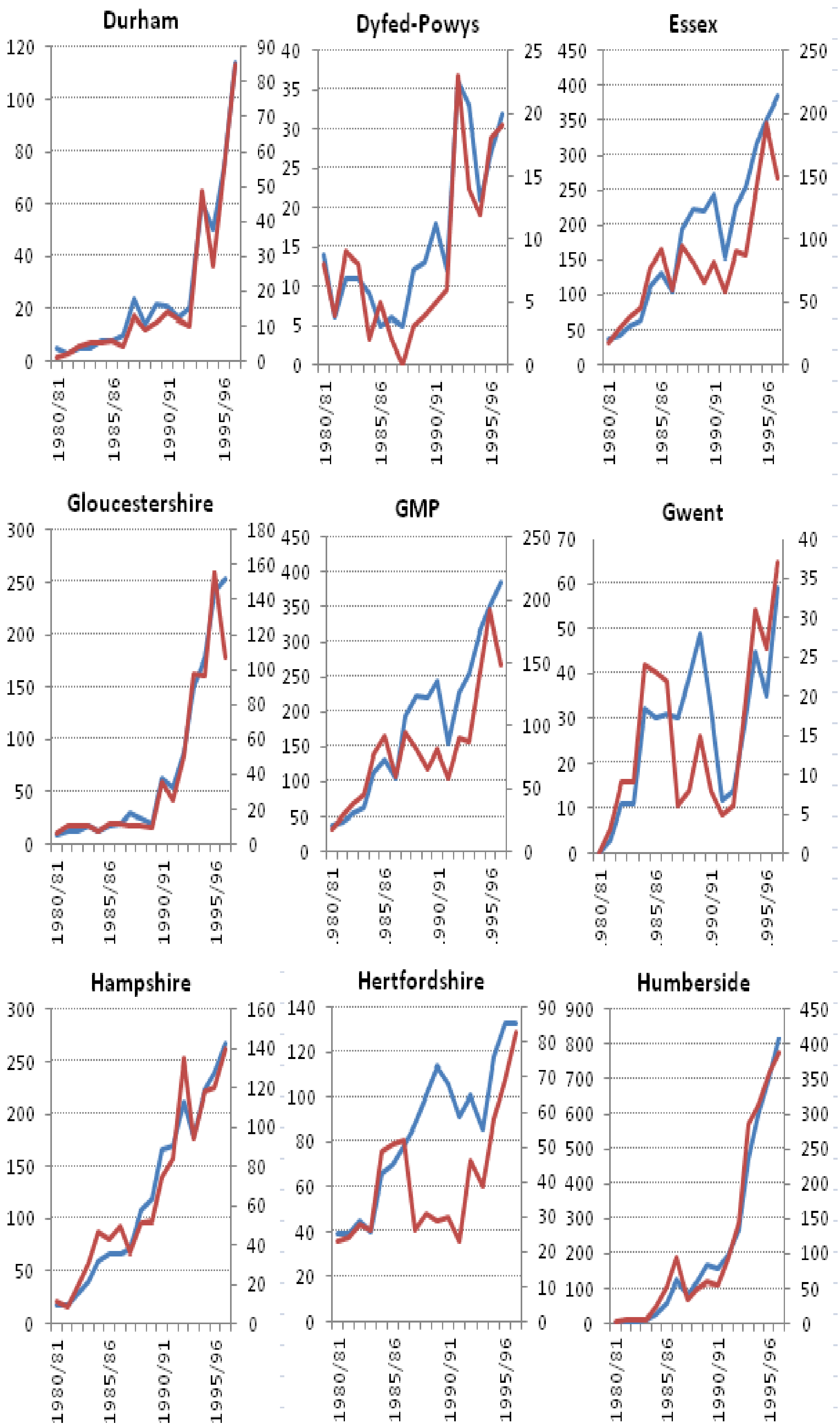

Surrey
14000
12000
10000
8000
6000
4000
2000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

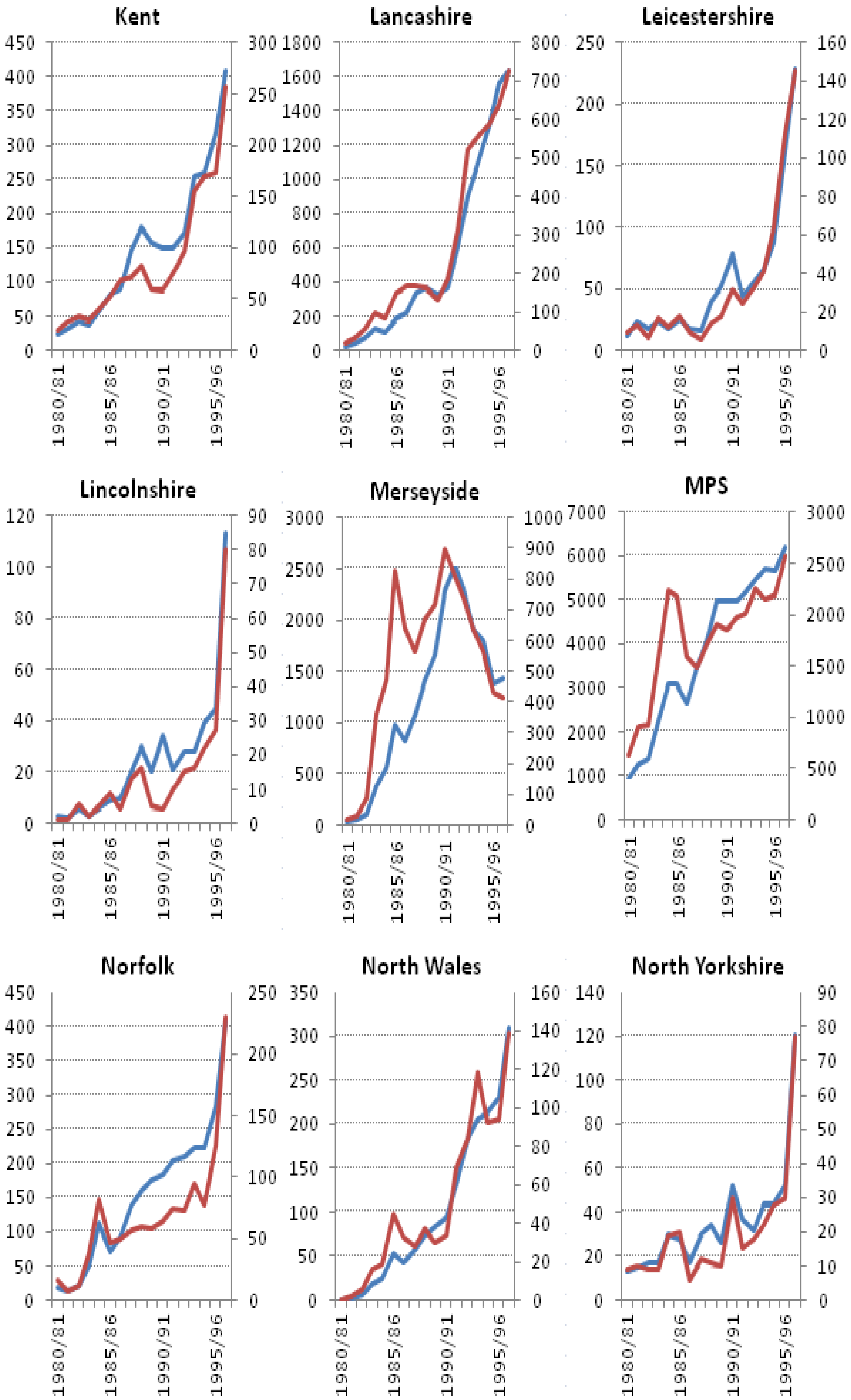

Sussex
35000
30000
25000
20000
15000
10000
5000
0
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

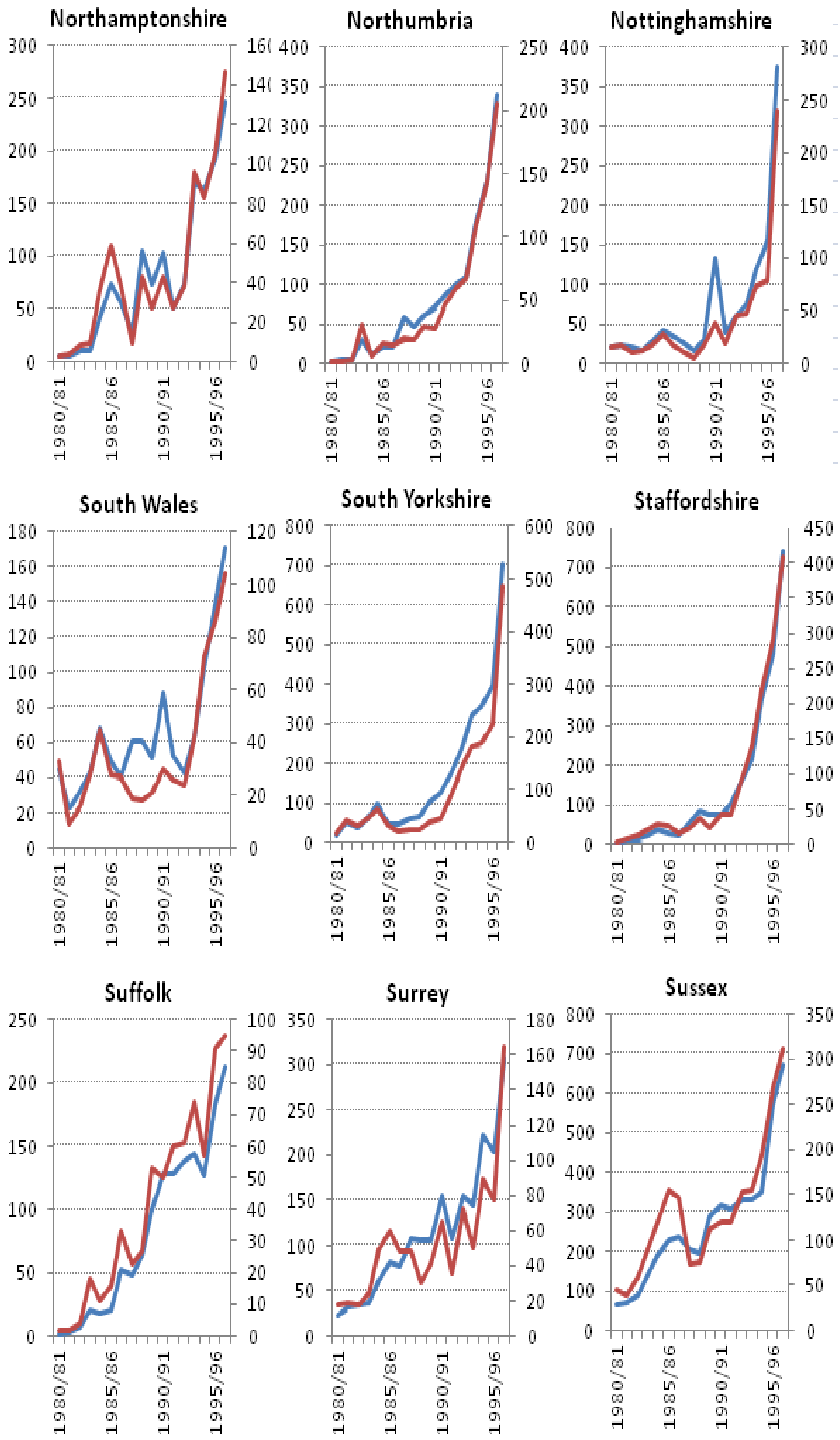

Thames Valley
Warwickshire
West Mercia
West Midlands
West Yorkshire
Wiltshire
1980/81
1983/84
1986/87
1989/90
1992/93
1995/96
1998/99

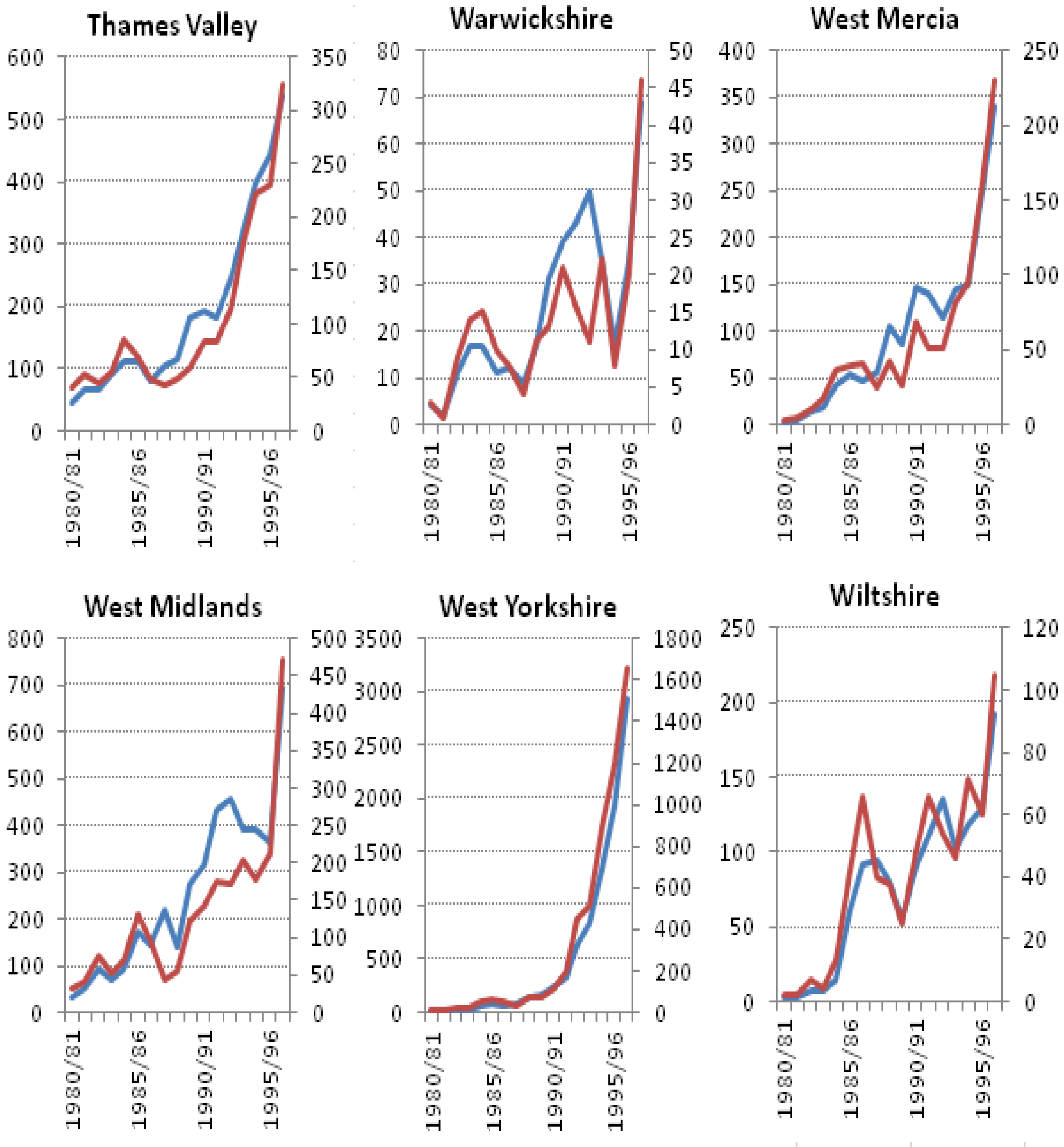
Appendix 3: Addicts Index trends, by police force area




Durham
1980/81
1985/86
1990/91
1995/96
Dyfed-Powys
1980/81
1985/86
1990/91
1995/96
Essex
1980/81
1985/86
1990/91
1995/96
Gloucestershire
1980/81
1985/86
1990/91
1995/96
GMP
Gwent
Hampshire
1980/81
1985/86
1990/91
1995/96
Hertfordshire
1980/81
1985/86
1990/91
1995/96
Humberside
1980/81
1985/86
1990/91
1995/96


Kent
450 400 350 300 250 200 150 100 50 0
300 250 200 150 100 50 0
Lancashire
1800 1600 1400 1200 1000 800 600 400 200 0
800 700 600 500 400 300 200 100 0
Leicestershire
250 200 150 100 50 0
160 140 120 100 80 60 40 20 0
Lincolnshire
120 100 80 60 40 20 0
90 80 70 60 50 40 30 20 10 0
Merseyside
3000 2500 2000 1500 1000 500 0
1000 900 800 700 600 500 400 300 200 100 0
MPS
7000 6000 5000 4000 3000 2000 1000 0
3000 2500 2000 1500 1000 500 0
Norfolk
450 400 350 300 250 200 150 100 50 0
250 200 150 100 50 0
North Wales
350 300 250 200 150 100 50 0
160 140 120 100 80 60 40 20 0
North Yorkshire
140 120 100 80 60 40 20 0
90 80 70 60 50 40 30 20 10 0
1980/81
1985/86
1990/91
1995/96


Northamptonshire
0 50 100 150 200 250 300
0 20 40 60 80 10(12(14(16(
1980/81 1985/86 1990/91 1995/96
Northumbria
0 50 100 150 200 250 300 350 400
0 50 100 150 200 250
1980/81 1985/86 1990/91 1995/96
Nottinghamshire
0 50 100 150 200 250 300 350 400
0 50 100 150 200 250 300
1980/81 1985/86 1990/91 1995/96
South Wales
0 20 40 60 80 100 120 140 160 180
0 20 40 60 80 100 120
1980/81 1985/86 1990/91 1995/96
South Yorkshire
0 100 200 300 400 500 600 700 800
0 100 200 300 400 500 600
1980/81 1985/86 1990/91 1995/96
Staffordshire
0 100 200 300 400 500 600 700 800
0 50 100 150 200 250 300 350 400 450
1980/81 1985/86 1990/91 1995/96
Suffolk
0 50 100 150 200 250
0 10 20 30 40 50 60 70 80 90 100
1980/81 1985/86 1990/91 1995/96
Surrey
0 50 100 150 200 250 300 350
0 20 40 60 80 100 120 140 160 180
1980/81 1985/86 1990/91 1995/96
Sussex
0 100 200 300 400 500 600 700 800
0 50 100 150 200 250 300 350
1980/81 1985/86 1990/91 1995/96


Thames Valley
Warwickshire
West Mercia
West Midlands
West Yorkshire
Wiltshire
1980/81
1985/86
1990/91
1995/96

Appendix 4: Studies with quantitative data on the criminality of opiate/crack users

Study	Nation	Sample	Brief Description	Crime Outcome
Adamson *et al.* (1998)	US	Treatment	Surveyed 64 individuals on the waiting list for methadone treatment. Looked at offending in the preceding seven days.	The mean financial gain from criminal sources was $1,079. Few gender differences were found. Those in employment did not earn significantly less from criminal activity. Nor did they spend significantly less on drug use.
Anglin and Speckart (1986)	US	Treatment	A sample of 671 methadone maintenance treatment (MMT) seekers from three different settings were interviewed with variable length follow up. Follow-up completion rate was 90%. Self-Reported offending data was collected the month before and after i) first addiction, ii) first MMT, iii) first MMT discharge and iv) last daily use.	Mean annual offending rates for the four stages were 2.3 offences in the month pre-addiction and 9.0 in the month after; 13.8 in the month pre-MMT and 4.5 in the month after; 5.9 in the month pre-MMT discharge and 7.8 after; 6.3 in the month before last use and 2.1 after (all crime days per month).
Ball et al. (1983)	US	Arrestees	Study of 384 Baltimore arrestees. Looked at self-reported criminality, but checked this against official records.	243 of the sample (all males) had on average committed more than 2000 offences per individual per year for the previous 11 years. Offending rates increased six-fold in addiction periods compared to non-addiction periods.
Bennett et al. (2008)	n/a	n/a	This study performed a systematic review of the literature, which revealed 30 studies investigating the link between drugs and crime; it then performed a meta-analysis of the strength of the relationship.	Odds of offending were three to four times greater for drug users than non-drug users. The odds of offending were highest among crack users and lowest among recreational drug users. This relationship held true across a range of offence types, including robbery, burglary, prostitution and shoplifting.
Best et al. (2001)	England	Treatment	The study investigates a cohort of 100 new treatment entrants in south London. 78 subjects reported heroin use in the month prior and 52 reported crack use.	56 reported acquisitive crime. Forms of crime most commonly engaged in were shoplifting, receiving stolen goods and theft. Crack users reporting the highest levels of drug expenditure and the most crime.
Boreham et al. (2006)	England & Wales	Arrestees	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6
Bukten (2012)	Norway	Treatment	A sample of 3,789 opiate users applying for substitute treatment were linked to a convictions register before, during and after treatment with zero attrition, but no control group. 40% had no convictions pre-treatment.	The cohort had 24,000 convictions in 3 years pre-treatment. Criminality dropped in the 3 months prior to treatment and stabilized at below half the pre-treatment level during treatment for those who remained in treatment. But the overall 'intention-to-treat' post-treatment level (i.e. including drop-outs) was above half the pre-treatment level.
Coid et al, 2000	England	Treatment	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6
Cox et al. (2007)	Ireland	Treatment	A survey of 404 drug treatment clients with self-reported criminal activity over the previous 90 days.	76% reported ever committing an acquisitive crime but only 28% said they had in the past 90 days (rates for dealing were much higher.)
Craddock et al. (1997)	US	Treatment	Incorporates two treatment-based studies with robust offending data. One was a sample of 9,989 (average age late 20s), who were mostly but not all heroin users; the other was a sample of 6,888 (average ag mid-30s) where the majority were crack-cocaine users.	For the first sample, 42% said they were involved in 'predatory' criminal activity in the year prior to treatment, meaning violence or serious acquisitive crime.
Davies et al, 2009	England & Wales	Treatment	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6

Study	Nation	Sample	Brief Description	Crime Outcome
Deschenes et al. (1991)	US	Treatment	A sample of 279 male heroin addicts admitted to methadone maintenance programs in Southern California were interviewed between 1978 and 1980.	The individuals reported more than 250,000 property crime-days during the course of their drug-crime careers, which resulted in 6,251 arrests. Analyses indicate that offense rates and related social/economic costs were at their highest during periods of addiction.
Farabee et al. (2001)	US	Treatment	A sample of 10,010 in-treatment individuals were asked about illicit activity and further analysis was then carried out on the 7,189 who admitted to offending. The sample was mainly crack users (14% used heroin only, 9.6% used heroin and crack and 14% used neither). They were asked about offending over their entire criminal career, whether they were using drugs during that entire period or not, and an average per-year rate was calculated using year of criminal onset and total offences - to avoid recent year bias.	They found that heroin users were more likely to start criminal careers after drug use than other types of drug user. They also found that heroin/crack were strongly associated with the likelihood of committing offences and were better predictors of the criminal career than demographic or background variables. The calculated overall annual offending rate (for 10 types of property crime) was 1.8 per year. This is markedly less than offending rates calculated in this paper, and the rates suggested by many other papers in this table. However - there are some crucial differences. Firstly, most of this sample were crack users and only a minority were heroin users, making it unrepresentative for the UK. Secondly, it's not clear - from our reading of the Farabee et al paper - whether the measure of crime frequency that was used was individual offences or days involved with crime and if the in-treatment rates of criminality were extrapolated across the entire career. If they were, and if days of crime were used, then this would be expected to produce a far lower estimate given the evidence that in-treatment offending rates are lower than pre-treatment and multiple offences like shoplifting can be committed in a single day. Plus, 347 individuals (3.5% of the sample) refused to answer the crime section of the survey. If these individuals were more likely to be high-offenders then this could also have a large effect given the fact that a small proportion of OCUs commit a majority of offences. Finally though - the Farabee et al paper calculates an offending rate across the criminal career for individuals currently in treatment for drug addiction. This paper attempts to calculate the offending rate for a given individual during a year in which they were an OCU - regardless of when their criminal career started and finished. The difference is subtle, but important. The Farabee et al rate, for example, would include the period after first offence but before first opiate/crack use, whereas ours would not.
French et al. (2000)	US	General Population	Econometric analysis using the National Household Survey on Drug Abuse (NHSDA) from 1993-95, which also has some criminal justice outcomes. Chronic drug users were separated from non-chronics but it wasn't possible to separate out opiate/crack users.	The results showed a consistent linear relationship between criminality and frequency of drug use.
Gossop et al, 2003	England & Wales	Treatment	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6
Hammersley et al. (1990)	Scotland	Community	Study of 210 teenage drug users (including non opiate/crack users) recruited from community setting.	Opioid users admitted to committing theft on an average of 37 days per year, but for those who were injecting that rose to 108. However, regression analysis suggested that the stronger direction of causality may be from crime causing drug use rather than the other way around.
Holloway and Bennett (2004)	England & Wales	Arrestees	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6
Hough et al. (2003)	England	Arrestees	Used a sample of 210 arrestees given a drug treatment and testing order (DTTO), meaning individuals that were referred to treatment due to an association between their arrest and drug use (mostly opiates/crack). 174 had criminal history on the Offenders Index and this group's convictions were analysed for 2 years pre- and post-test.	80% of the sample, many of whom had long criminal histories were re-convicted within the two year period. There were marked differences in conviction patterns between areas, with individuals from Liverpool showing almost a constant conviction rate regardless of the timing of the DTTO, whereas individuals from Gloucester showed almost a doubling in conviction rates in the year prior to the DTTO being given, and a large reduction two years latter. This possibly suggests the different stages of the epidemic cycle. The Liverpool group would likely have been more established users, given that the epidemic was well passed its peak there by this time, whereas it was much closer to peak in Gloucester.
Hucklesby et al. (2007)	England	Arrestees	1,828 defendants testing positive for class A drugs between May 2004 and July 2005 were matched to the Police National Computer and offending histories checked.	All but 18 of the 1,828 had previous convictions. The majority (1089) had more than 50 convictions and the mean number of total convictions was 170. The mean number of years between first conviction and appearance in the study was 14 years.
Hutchinson et al. (2000)	Scotland	Half treat-ment, half-community	Self-reported data on illegal income used to pay for drugs was gathered from 954 current injecting drug users (90% were heroin users).	Four-fifths of the sample self-reported an illegal income, and of these, 69% said their main income source was acquisitive crime.

Study	Nation	Sample	Brief Description	Crime Outcome
Inciardi (1979)	US	Community	Looked at official and self-reported criminality in a sample of 356 active heroin users, as well as the ordering of the drugs-crime link.	97.4% of the sample reported criminal activity (80.5% said this was for the purpose of funding a drug habit.) The cohort self-reported 118,134 offences in the previous year (avg 332), 27,464 of which were classed as serious (avg 77).
Jarvis and Parker (1989)	England	Treatment / Prison-based	An analysis of 46 London-based heroin users, looking at convictions as well as self-reported criminality and drug use.	Though crime often preceded drug use, the sample's conviction rate more than doubled following the onset of regular heroin use. The sample admitted to spending £23,000 a week on drugs yet their total legitimate income was just £2100 per week.
Kaye et al. (1998)	Aus	Prison / Community	A sample of 200 prison inmates and 200 community-recruited methadone maintenance patients were compared criminality measures, in two groups: those who did crime before starting to take heroin (labelled `primary anti-socials') and those who took heroin before starting on crime (secondary anti-socials).	98% of the primary anti-socials and 93% of the secondary anti-socials had ever been arrested. There were no significant differences in the percentage chances of ever being convicted for most non-violent, acquisitive offences (fraud, dealing, burglary, minor theft) but the primary anti-socials were statistically signicantly more likely to have been convicted of a violent offence (assault, criminal damage, arson and robbery).
Kinner et al. (2009)	Aus	Treatment / community	Structured, face-to-face interviews were conducted with 909 regular injectors from every (state-)capital city in Australia, between June and August 2007, as part of the annual Illicit Drug Reporting System (IDRS). Criminal activity in the past month was assessed.	43% reported recent past-month criminal activity. Those who had committed crime recently were younger, exhibited riskier patterns of drug use, reported more drug related problems and were more likely to exhibit significant psychological distress.
MacCoun et al. (2003)	US	Arrestees	Describes results from the Arrestee Drug Abuse Monitoring Program (ADAM).	Across 35 US cities in 1998, 40-80% of male arrestees tested positive for drugs at arrest. 22%/33% of Federal/State inmates reported being under the influence of drugs at the time of their offence, rising to 40% for state inmates convicted f acquisitive crimes. 27% of robbery ofrfenders and 30-32% of burglary offenders said they committed their offence to buy drugs.
Maher *et al*. (2002)	Aus	Community	Study of 202 heroin users from the community (15% in treatment) in south west Sydney.	70% said they were actively involved in property crime, with an average of $534 generated per week from acquisitive crime. But still that only accounted for 38% of the money spent on drugs (44% came from dealing).
Makkai (2001)	Aus	Arrestees	1,408 adult males detained by police were approached. Eighty-four per cent agreed to complete an interview and 70% provided a urine specimen to test for drug use.	Around three-quarters tested positive. Cannabis was most likely, followed by opiates, benzodiazepines, and then amphetamines. One-third tested positive to multiple drug use. Those who tested positive to opiates were more likely to be charged with property offences while those who tested positive to cannabis were more likely to be charged with a drug offence.
McIntosh et al. (2007)	Scotland	Treatment	1,033 individuals were surveyed on criminality pre- and post-treatment entry in 2001/2. (But suffered attrition, only 70% did all the follow-up surveys.)	35.1% said they had committed acquisitive crime in the past three months pre-treatment. Authors concluded that treatment is effective in reducing offending "not by altering criminal activities directly but by reducing their consumption of illegal drugs."
Mott (1986)	England	CJS	87 notified addicts were identified from burglars prosecuted in London and Merseyside and compared to age-matched controls for previous criminal history.	The proportion of convicted burglars that were notified as addicts (likely to be a marked underestimate of the true proportion) ranged from 1-15% in Merseyside and 3-11% in London. The Merseysiders (where the epidemic was new and the OCU population young) had a similar rate of previous offending to controls. The Londoners (who were older and more established users) had an offending rate 35% higher than controls.
Packer et al. (2009)	England	Arrestees	Used a survey of 50 drug using offenders attending a Birmingham Drug Intervention Programme clinic under the terms of a Drug Rehabilitation Requirement (DRR). 70% had used heroin on a mean of 11.9 days, and 54% had used crack cocaine on a mean of 11.1 days in the last month.	32% reported acquisitive crimes within the last 90 days, with a mean number of 23.7 offences . The mean number of previous convictions was 23.3 There were significant positive correlations between intensity of acquisitive crime in the last 90 days and intensity of heroin use and crack use, and drug spend.
Parker and Newcombe (1987).	England	Arrestees	The authors looked at a group of arrestees in the Wirral to see what percentage were known drug users. They then checked the conviction history of those individuals.	Of all burglary offenders, 55% were known drug users, and drug users were over-represented in all crime types tested except criminal damage.
Roe and Ashe (2008)	England & Wales	National	This was one of the studies used in the final model hence is described in detail in Appendix 6.	See Appendix 6
Ross et al. (2002)	Aus	Treatment	535 treatment-seeking heroin users plus 80 recruited from the community were surveyed on their offending in the previous month.	Over half admitted to committing a crime in the previous month. Property crime (39%) was the most common offence followed by dealing (21%).
Schwartz et al. (2008)	US	Treatment	Compares 169 treatment-seeking opioid-addicted individuals to 74 not seeking treatment on self-reported drug use and criminality in the previous 30 days.	Finds mean illegal income from the in-treatment sample to be $537 in the past 30 days compared to $1100 for the out-of-treatment sample. Comparison of lifetime arrests showed 6.79 for the in-treatment group and 7.66 for those out-of-treatment.
Skodbo et al. (2007).	England & Wales	Arrestees	Analysed convictions data for the previous three years for individuals testing positive for heroin, cocaine or crack on charge (n=7,727) and arrest (11,015).	Mean number of convictions per individual over the three-year period was 11.3 for the test on charge group and 8.8 for the test on arrest group.
van der Zanden et al. (2007)	Nether-lands	Treatment	A sample of 51 opiate users receiving methadone maintenance treatment were asked to report their offending levels in the previous month.	50% reported acquisitive crime with an average of 64 offences per individual for the month (mostly shoplifting). The majority said they committed the offences in order to get money to pay for drugs.

Appendix 5: Results of the evidence review on OCU exit rates

To decide on the actual exit rate percentages, a systematic review was located (Calabria et al, 2010) from which exit rates could be calculated and this was supplemented with one additional study from after the review period (Grella & Lovinger, 2011). The results of this process are shown in the table below:

Table A1: Results from studies with data on OCU exit rates

Study	Country	Follow-up (in years)	Total		Followed-Up Sample	
			Initial Sample	Remission Proportion	Sample	Remission Proportion
Okruhlica et al, 2002	Slovakia	3	351	0.356	245	0.51
Teeson et al, 2008	Australia	3	615	0.54	429	0.78
Lerner et al, 1997	Israel	5	72	0.569	44	0.932
Mufti et al, 2004	Pakistan	5	100	0.16	70	0.229
Verachai et al, 2003	Thailand	5	278	0.655	257	0.712
Byrne, 2000	Australia	8.6	86	0.36	79	0.394
Madruga et al, 1998	Spain	12	296	0.449	189	0.704
Goldstein & Herrera, 1995	US	22	1013	0.183	243	0.761
Hser, 2007	US	33	581	0.179	242	0.43
Rathod, 2005	UK	33	86	0.419	45	0.8
Grella & Lovinger, 2011	US	30	914	0.289	343	0.086

(Remission proportion is the proportion of the sample that are abstinent. It differs between `Total' and `Follow-Up' due to the numbers who are not followed up. So although 51% of the follow-up sample in the top study were in remission this represented just 36% of the original sample. Note also that the Grella and Lovinger study was added to this table separately using methodology described below.[141])

Sources: Calabria et al, 2010; Grella and Lovinger, 2011)

There are two important conclusions to be taken from this table for the purposes of constructing the model:

i) the numbers of individuals *not* followed up (largely due to the fact they'd died) can be considerable, particularly in the longer term studies. For example, in Hser et al, 2007, 284 of the original 581 sample had died by 33-year follow-up; and 428 of 914 had died by 30-year follow-up in the Grella & Lovinger sample; which means that premature mortality is likely to be a crucial factor in the exit rate.

ii) the shorter studies report higher annualised exit rates, including both those who quit and those who die.

[141] The figures for Grella & Lovinger, 2011 were added separately. This was a 30-year follow up study that broke the population into four categories with associated percentages, and percentage of the group still using after 30 years shown in brackets: rapid decrease (24.6% of cohort, 0% still using), moderate decrease (14.7%, 0%), gradual decrease (35.2%, 7%), no decrease (25.5%, 80%).

To see this latter point more clearly, consider the table below, which is calculated from the figures in the table above:[142]

Table A2: Calculated quit rates from published studies

Study	Proportion Still Using at Follow-Up (Minimum)	Implied Annual Exit Rate	Average Annualised Quit Rate	Weighted Average Annualised Quit Rate
Okruhlica et al, 2002	34.2%	30%	32%	35%
Teeson et al, 2008	15.3%	46%		
Lerner et al, 1997	4.2%	47%		
Mufti et al, 2004	54.0%	12%		
Verachai et al, 2003	26.6%	23%		
Byrne, 2000	55.7%	7%	8%	9%
Madruga et al, 1998	18.9%	13%		
Goldstein & Herrera, 1995	5.7%	12%		
Hser, 2007	23.7%	4%		
Rathod, 2005	10.5%	7%		
Grella & Lovinger, 2011	8.60%	8%		

Sources: Calabria et al, 2010; Grella and Lovinger, 2011)

For the studies that had follow-up periods of five years or less, the average annualised exit rate was around a third per year, whereas studies that looked at periods over five years had overall exit rates of around 8-9%. This therefore concurs with the evidence that quit rates are higher earlier in OCUs' careers and that as career length increases a smaller and smaller proportion will achieve abstinence each year. It also means that treatment-based studies will likely report average career lengths with an upward bias, as many will have quit on their own before requiring the need for treatment (see also Best et al, 2006 on this).

The above table also suggests that using exit rates between 5-13% is a sensible estimate given that the model covers a period of forty years and the average rate for long-term studies is 9%.

To obtain usable parameters for constructing s-shaped exit rates that take into account both the apparently higher exit rate in the early years and the increasing mortality rate in the later years, we examined the Hser et al, 2007 sample in more detail. The Hser sample was followed up at 11, 22 and 33 years, with results below:

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[142] The calculations are, for the top line:
Proportion still using at follow up: ((1-0.51)*245)/351
Annual Exit Rate: 1-(34.2%^(1/3)

Table A3: Data from the Hser et al, 2007, study

	1974-75 Follow-Up		1985-86 Follow-Up		1996-97 Follow-Up	
	Total	Interviewed	Total	Interviewed	Total	Interviewed
	581	439	581	354	581	242
Inactive Use - urine negative	28.60%	37.85	25%	41%	23.20%	55.80%
Urine positive	23.10%	30.50%	19.40%	31.95	8.60%	20.70%
Refused urine test	6.20%	8.20%	4.80%	7.90%	4%	9.50%
Incarcerated	17.70%	23.50%	11.70%	19.20%	5.80%	14%
Dead	13.80%	-	27.70%	-	48.90%	-
Unknown	10.70%	-	11.40%	-	9.50%	-

Source: Hser et al, 2007

The figures in the table above were used to calculate the table below. It was impossible to be sure how many of those who either refused a urine test, were incarcerated or couldn't be located, were still using drugs at that point. The maximum estimates in the table below assumes all of these are, the minimum assumes none of them are:

Table A4: Exit rates calculated from Hser et al, 2007, study

	Original Sample 1962-64	Follow-Up		
		1974/5	1985/6	1996/97
Years On	0	11	22	33
Mean Age	24	35	46	57
Survived	581	501	420	297
Died	0	80	161	284
Death rate (if fixed from previous period)	0	1.30%	1.60%	3.11%
Still in OCU population	581	335	275	162
% Still OCU (max)	100%	57.7%	47.3%	27.9%
% Still OCU (min)	100%	23.1%	19.4%	8.6%
% Still OCU (avg)	100%	40.4%	33.4%	18.3%
Implied exit rate, including both cessation and death (total period)	0%	8%	5%	5%
Implied exit rate including both cessation and death (from last period)	0%	8%	2%	5%

Source: Hser et al, 2007

The results above lend further support to the hypothesis that exit rates decrease over time generally as the exit rate is higher in the first eleven years than in the subsequent two 11-year periods. But the sharply increasing death rate in the final period suggests that the overall survival curve for the cohort may be s-shaped, with a very low exit rate during the middle period, when the early quitters have been whittled out but when the OCUs are still young enough that the higher mortality rates have not been reached.[143]

We used the results above to construct two s-shaped exit rates for testing (labelled “Hser-Based Exit Rate” in the final table.) This was done by matching the survival rates of the population to the average figures recorded in the third-to-last row of this table. Care was taken to ensure this was done correctly. For example, it is also important to recognise that the study does not start from career initiation. The average lag between drug initiation and entry to the Hser study was around 5-6 years, meaning that the 33-year follow-up is effectively testing exit rates for career years 7-40. For the very early years of career we assumed – in line with the Kaya et al/Vietnam evidence – a decrease exponentially from high levels (around 30%) in year one.

[143] The mortality rates from the table are similar to those found by Cornish et al, 2010 (http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2965139/) in a UK study. Their mortality rates, structured by age rather than by length of career, were as follows: <30 = 0.74, 30-39 = 0.89, 40-49 = 1.4, >50 = 3.26.

Appendix 6: Detailed description of the short-listed studies used in the model.

1) NTORS

The National Treatment Outcome Research Study (NTORS) recruited 1075 individuals at treatment intake in 1995. The sample was broadly, nationally representative – being taken from agencies across England and Wales and with a breakdown of treatment modalities in line with the national picture. The recruits were mainly men (74%), heroin users (87%) and had an average age of 29.3 years. Half the group (n = 541) reported committing acquisitive crime in the past three months and overall, the cohort self-reported 27,787 separate acquisitive offences in that period. (The study did not ask about violence offences). This is an average of 26 offences per person in the total cohort (including those that didn't offend at all) or 51 per person for those who admitted some offending. Three quarters of the crimes were committed by 10% of the sample. Regular heroin use was the most powerful predictor of committing offences. These results are summarised below (first four columns). The final two columns are manipulations performed for the modelling in order to convert the results into offending rates per OCU per year.

Table A5: Offending data from NTORS

Offence	N	% of total sample (n=1075)	Total crimes reported in the last three months	Estimated self-report crimes in a year (x4)	Per Person (in whole sample)
Shoplifting	406	37.8%	21,479	85,916	79.9
Fraud	160	14.9%	3,253	13,012	12.1
Burglary	133	12.4%	1,301	5,204	4.8
Robbery	58	5.4%	390	1,560	1.5
Other Theft	51	4.7%	1,364	5,456	5.1
Total			**27,787**	**111,148**	**103.4**

Source: Stewart et al, 2000

Before proceeding it is important to deal with a potential criticism of the above methodology: that multiplying up the offending immediately prior to treatment may over-estimate annual offending if OCUs tend to enter treatment off the back of a particularly pronounced crime wave. This is certainly a plausible possibility, but for the most part it doesn't look to be supported by the facts, which is why we've not made any adjustment for it here (or in relation to DTORS, see below).

In DTORS, respondents were specifically asked whether they had consumed more drugs and committed more offences in the last four weeks compared to normal. Only 10% said they had consumed more drugs in the previous four weeks than normal, and 24% said they had committed more offences. By contrast, 40% said they had taken *fewer* drugs than normal in the last four weeks and 44% said they had committed fewer offences; 50% said their drug use had been about the same as normal and 32% said the same for offending levels. Similar results were reported in Coid et al (2000) and Bukten *et al*, 2013. Only 25% of the sample said that their offending had increased in the six months before seeking treatment whereas the rest said it had stayed the same or decreased.

In a recent paper, the National Treatment Agency also studied this issue. They matched a treatment-seeking sample with criminal justice system data to look at the pattern of convictions in the year prior to treatment to see if the number of convictions in the four weeks prior to treatment was representative. They found that the total number of convictions for the sample was far higher in the four weeks before treatment than for the rest of the year and that extrapolating the 4-week period up to the year would lead to about twice as much crime being estimated as actually occurred. However, further investigation suggested that this was not in fact due to individuals becoming more criminally active in the period before treatment. *For any given individual,* the annual rate of conviction in the 4 weeks prior to treatment was very similar (1.35) to the annual conviction rate for the *two years* prior to treatment (1.30). The reason there were more convictions immediately before treatment, for the sample as a whole, was due to the high number of people convicted just prior to treatment, not because these individuals had an escalation in offending rates. The reason for this is simple. With the introduction of the Drugs Intervention Programme in 2003 individuals convicted of acquisitive offences were very likely to be referred to treatment, hence a spike in convictions immediately prior to treatment entry should be expected. This does not necessarily imply that individuals' actual offending is likely to spike and data, on the whole, suggests it does not. So for the model, the shorter time periods of offending measured – three months for NTORS, four weeks for DTORS – are simply multiplied up to annual figures with no further adjustment.[144]

Of the 1075 individuals surveyed in NTORS, 799 were also matched to the Offenders Index database (no offences were recorded for the other 276) and these individuals were responsible for 1662 proven offences in the year prior to intake, an average of 1.55 per person for the cohort as a whole.

The study also measured how the number of self-reported and proven offences changed after treatment entry (though due to the lack of a robust control group we cannot be sure that the changes were due to the treatment

[144] It is important to note that this conclusion only applies to the type of extrapolation performed for this model. That is, the evidence presented here shows that there does not seem to be a case for adjusting (downwards) the criminality from the period immediately before treatment when applied to an annual rate of offending for someone who we know is using opiates or crack at that point. That does not make it correct to extrapolate this rate across the entire criminal career of someone who uses opiates or crack at some point during that career. The distinction is subtle, but there is a very large difference, given the evidence that users cycle in and out of addiction periods and that crime levels can differ hugely between these periods; and that criminality can start before drug use. Farabee et al, 2001, show that annualized crime rates for drug users (albeit largely cocaine users rather than heroin users) aggregated across entire careers will be much lower. But for our purposes these rates would not be correct to use as they would include periods of time during which the individual would not be part of the OCU population.

itself.) For acquisitive crimes the study found a 70% reduction in self-reported acquisitive offending in the first year and a 22.2% reduction in proven offences. Part of the reason for this difference is likely due to the fact that only 83% of the original 1,075 individuals were available for interview at follow-up and analysis shows this group tended to be lower-rate offenders than those who were not available. Note that the sample was also followed up after two years (self-report and proven offending) and five years (just proven offending). The number of proven offences fell over this period so that the five-year level of acquisitive offences was only 23% of the pre-intake level. In other words, the study shows that offending fell pre-treatment to post-treatment, but that a) we cannot say for certain this was due to treatment, b) even the uncontrolled reduction for the first year is probably closer to 20-25% than the very high figs suggested by the self-report data. But equally the proven offence data also suggest that offending continued to fall for several years after first attendance at treatment, though again we cannot say that the treatment itself was the cause of this.

Due to these issues, for the model we use the self-report, pre-treatment (full sample) offending rates, but we use the reductions from the proven offending. The next question was whether the reduction should be averaged out over the entire five-year follow-up or limited to a shorter period. The crucial question here is whether individuals would still be considered OCUs at five-year follow up. It seems likely that the large reductions seen at the five-year follow up would be due in part to some of the original users become completely drug-free, hence these users would have dropped out of the OCU population, so their crime reduction should no longer be included. We therefore use only the crime reduction from the first two years, where it seems likely that they would still be registered to treatment services and therefore counted in the OCU population. The burglary figures were adjusted to exclude commercial burglary, as above, and fraud and shoplifting offences were removed. This gives the following results:

Table A6: NTORS offending rates

	NTORS	
Average Annual Offences per OCU	Out-of-Treatment	In-Treatment
Total	103.4	67.9
All Acquisitive	91.3	42.8
All CSEW Acquisitive (i.e. with shoplifting, fraud and commercial burglary removed).	8.4	4.9

Source: Stewart et al, 2000

2) DTORS

The Drug Treatment Outcomes Research Study (DTORS) recruited a sample of 1,796 adults seeking treatment for a drug problem across 342 treatment facilities in England and Wales. Though heroin was the predominant drug used by the cohort, it also contained around 15% of individuals whose primary drug problem related neither to heroin or crack but another drug (cannabis, alcohol, ecstasy etc). As these drugs are generally less associated with acquisitive offending than heroin and crack, it means that the cohort's average offending rates, calculated below, are actually quite conservative for the model.

The cohort self-reported offending for the four weeks prior to treatment, and this was broken down into a detailed list of offence types (see Davies et al, 2009, p10). The cohort was then followed up and self-reported offending in a 4-week period 3-5 months later and 11-13 months later was captured. Overall offending fell 37% between baseline and first follow-up but then rose again so that by second follow-up offending was only 10% lower than at baseline. The published results are shown below:

Table A7: DTORS offending data

	Number of self-reported offences in previous 4 weeks								
	Baseline			First follow up			Second follow up		
	n	mean	se	n	mean	se	n	mean	se
Shoplifting	1,754	3.71	0.59	1,064	1.63	0.68	479	3.46	2.6
Begging	1,772	0.47	0.08	1,067	0.27	0.1	483	0.15	0.07
Buying & selling stolen goods	1,749	2.43	0.42	1,066	1.79	1.11	482	0.63	0.19
Drug dealing	1,761	2.13	0.5	1,067	2.28	1.27	481	4.52	2.99
Prostitution	1,772	0.49	0.22	1,070	0.09	0.04	480	0.02	0.01
Theft of vehicle	1,769	0.05	0.01	1,070	0.02	0.01	482	0.02	0.01
Theft from vehicle	1,768	0.15	0.02	1,068	0.05	0.02	483	0.01	0.01
House burglary	1,771	0.03	0.01	1,067	0.02	0.01	482	0	0
Business burglary	1,768	0.19	0.04	1,069	0.08	0.02	483	0.17	0.11
Violent theft	1,770	0.06	0.02	1,070	0	0	482	0.01	0.01
Bag snatch	1,772	0.07	0.02	1,071	0.02	0.01	481	0.03	0.02
Other stealing	1,768	0.38	0.06	1,067	0.21	0.05	481	0.23	0.11
Cheque or credit card fraud	1,771	0.08	0.03	1,070	0.01	0	483	0.01	0.01
Other violent crime	1,772	0.11	0.01	1,070	0.08	0.02	483	0.09	0.04

Source: Davies et al, 2009

However, like NTORS, the study has several weaknesses. It has no control group, meaning that the result cannot be attributed to the treatment itself with any certainty. It also suffered a very high attrition rate. At first follow-up only around 1,070 of the original 1,796 answered the offending questions and by second follow up the number had reduced to around 483. Obviously this risks biasing the results as it seems plausible that the drug users who offend most may be those most likely to drop out. The study authors did use a complicated weighting system to try and cope with this shortcoming, but it is hard to judge how successful this was. Finally, the DTORs team elected to exclude outliers from the study – those that claimed to have committed a disproportionately high number of offences were removed from the analysis. This is obviously a sensible thing to do in circumstances in which the distribution of the variable of interest is normal. But all the evidence collected for this study would suggest that the distribution of offending amongst OCUs is very far from normal. It is instead highly skewed. A few offenders generally commit a very high percentage of offences and this is a very consistent finding across studies. In other words, there are always a few high-crime outliers and they provide a high proportion of offences. By excluding these individuals DTORs will provide a marked under-estimate for offending of the cohort as a whole. Given that the primary purpose of DTORS was to look at the *change* in offending across individuals, this is perhaps not a huge problem for the study itself. But for use in the model to capture overall OCU offending it again means that our estimate is likely to be an under-estimate.

Unlike NTORS, DTORS also asked about non-acquisitive offending including violence, prostitution, begging etc, so the total crimes and the acquisitive total are different. For the CSEW acquisitive category, shoplifting fraud and commercial burglary were removed along with all other offences that would not be recorded on a crime victimisation survey (like handling stolen goods).

Table A8: DTORS offending rates

	DTORS	
Average Annual Offences per OCU	Out-of-Treatment	In-Treatment
Total	135.0	90.9
All acquisitive	92.2	47.1
All CSEW acquisitive	9.6	6.4

Source: Davies et al, 2009

3) Coid et al (2000)

This study surveyed 221 opiate-dependent treatment seekers between 1995 and 1997 in a socio-economically deprived area of inner London (so the study was not nationally representative). Virtually all admitted to previous criminal activities but 15% had managed to support their habit in the six months before presentation by legal means. The average subject had spent over £10,000 a year on opiates obtained from illegal sources. The raw results relating to pre-treatment crime are shown below:

Table A9: Offending data from Coid et al, 2000

Crime committed by pre-treatment sample (n=221)	Ever		Last 6 Months		Mean Days in last 6 Months	Last month		Mean Days in last Month
	N	%	n	%	N	n	%	n
Theft/shoplifting	183	82.8%	101	45.7%	82	82	37.1%	16
Dealing	170	76.9%	91	41.2%	78	65	29.4%	14
Fraud	106	48.0%	36	16.3%	29	17	7.7%	9
Burglary	94	42.5%	18	8.1%	45	13	5.9%	10
Violence	84	38.0%	14	6.3%	6	9	4.1%	13
Benefit fraud	79	35.7%	47	21.3%	134	36	16.3%	26
Vandalism	65	29.4%	3	1.4%	4	2	0.9%	1
Other	55	24.9%	40	18.1%	40	30	13.6%	17
Robbery	45	20.4%	7	3.2%	18	4	1.8%	9
Prostitution	36	16.3%	14	6.3%	101	12	5.4%	17

Source: Coid et al, 2000

These results were converted into annual crime totals by taking the conservative assumption that `crime days' accounted for only one offence for each crime type admitted to. So by multiplying the mean number of crime days by the number of offenders for each offence and then multiplying by 12 for the `last month' columns and by two for the `six month' columns, we get two estimates for the total number of crimes in the past year. One extrapolated from the past month and one extrapolated from the past six months. By dividing by 221 (the number in the sample) we get averages per user – as shown below:

Table A10: Offending rates from Coid et al, 2000

	Annual Crimes Per Person		
	6-month Extrapolation	1-month Extrapolation	Average of the two
Theft/shoplifting	75.0	71.2	73.1
Dealing	64.2	49.4	56.8
Fraud	9.4	8.3	8.9
Burglary	7.3	7.1	7.2
Violence	0.8	6.4	3.6
Benefit fraud	57.0	50.8	53.9
Vandalism	0.1	0.1	0.1
Other	14.5	27.7	21.1
Robbery	1.1	2.0	1.5
Prostitution	12.8	11.1	11.9
Total	**242.2**	**234.0**	**238.1**

Source: Coid et al, 2000

Two-thirds of the sample said there was a “strong link” between their drug habit and criminality with 50% saying that their criminal activities were now carried out solely to fund their drug habit.

The above table shows two important things. Firstly the general level of criminality is extremely comparable with our other treatment-sample sources, with very high levels of shoplifting and dealing and relatively lower levels of more serious acquisitive crime like burglary. But it also shows that if there is an increase in offending prior to treatment, that increase appears to be concentrated into a longer period than just a month – indeed, the six-month extrapolation actually gives a higher total of crime than the one-month extrapolation.

Using a sub-set of the original sample, the study also measured the change in crime levels pre and post methadone maintenance treatment. Follow-up interviews were conducted at one month post treatment presentation and six months post. They found that heroin use fell by 50% in the sample, but that use of other drugs remained at pre-treatment levels. Burglaries and thefts were also reduced by half and the impact on dealing was even greater. But there were no significant changes in fraud, robbery and prostitution. Again, the study suffered from two major weaknesses: a lack of a control group (meaning that we should be cautious about attributing the changes directly to the methadone maintenance treatment) and attrition (35 users dropped out who had similar characteristics on the whole but, by the very fact that they dropped out may have had higher crime levels in the follow-up period). These two issues notwithstanding, the reductions in crime are shown in the table below:

Table A11: Offending rates pre- and post-treatment from Coid et al, 2000

	Crime Days in Last 6 Months		
	Pre-treatment	Post-treatment	% reduction
Theft	44.0	20.6	-53.2%
Burglary	3.4	1.2	-64.3%
Fraud	2.4	7.7	216.9%
Benefit Fraud	27.0	31.9	17.9%
Robbery	3.7	1.2	-68.8%
Dealing	56.4	19.8	-64.8%
Sex Work	17.4	19.1	9.8%
Other Crime	13.9	0.1	-99.4%

Source: Coid et al, 2000; shaded boxes indicate statistically significant changes.

For the model then, we use the crime rates for the complete sample and the reductions from the table above to calculate an offending rate for the out-of-treatment population. As before, for `all acquisitive’ crime we used just theft/shoplifting, burglary and robbery (as fraud and dealing are not included in over-arching theft or acquisitive crime categories in police recorded crime or the CSEW). For the `CSEW acquisitive’ category we removed commercial burglary (via the method outlined above) and shoplifting. The latter was achieved by presuming that the breakdown of the theft/shoplifting category was similar to the breakdown between other theft and shoplifting in NTORS (which would suggest that 94% of this category was shoplifting and 6% was theft).[145] As before, all crime types that wouldn't be surveyed on the CSEW were removed for the final model, to give the final result in the table below:

Table A12: Final offending rates from Coid et al, 2000

	Coid et al.	
Average Annual Offences per OCU	Out-of-Treatment	In-Treatment
Total	238.1	143.6
All acquisitive	81.8	37.2
All CSEW acquisitive (i.e. with shoplifting, fraud and commercial burglary removed).	8.7	5.7

Source: Coid et al, 2000

4) <u>The Arrestee Survey</u>

The Arrestee Survey, which took place between 2003 and 2006, asked a nationally representative sample of arrestees aged 17 and over in England and Wales about their drug use and criminality. Though the survey was nationally representative, weighting systems were used to compensate for greater non-response amongst certain groups. The responses were weighted by the inverse of the number of arrests the offender had previously experienced. This compensates for non-equal probabilities of selection arising from the fact that some offenders are more likely to be arrested than others and would therefore be more likely to be selected in the survey (see Stevens, 2008).[146]

145 Note that using DTORS would give a much higher proportion of theft, around 11%, so again the approach we have taken is conservative.

146 In any given year, offenders who get arrested more frequently would be more likely to be sampled in the survey so without this correction the estimates for total crime committed by arrestees would be biased upwards. Note though that this correction only applies to the sampling frame for the scaling up process. The fact that drug users –according to Stevens' 2008 paper – might have a different ratio of arrests to total offences from other individuals is not corrected by the weighting. This is because, as we are using self-report rather than arrests as the offending measure (so as to map to total CSEW crime), any difference in that ratio is not actually a problem. It is corrected by having the offenders themselves report on their total crimes. So it allows for a drug-misusing offender to self-report a lower total volume of crime per arrest then other offenders.

For use in the model, it was important to decide which arrestees were OCUs. This was done using a question on the survey in which participants responded yes/no to each of the following:

- use of heroin or crack cocaine at least once a week in the past year;
- use of heroin or crack cocaine more than twice a week in the past year;

As our interest here is on capturing relevant offending rates for any type of OCU, regardless of the frequency of offending, the widest definition was used: use of heroin/crack at least once a week in the past year.

The survey asked questions regarding prevalence and volume of offending in relation to the main acquisitive crime types, from which weighted, annual volumes were calculated and hence average annual rates per OCU. The weights ensured representativeness as explained above. The results are shown in Table A13 below:

Table A13: Arrestee Survey offending rates

Arrestee survey annual offending rates	
Domestic Burglary	1.38
Commercial Burglary	2.59
Theft of Vehicle	1.57
Theft from Vehicle	3.49
Theft from Person	1.49
Commercial robbery	0.42
Personal robbery	0.42
Other Theft	25.5
Violence	1.3
Criminal Damage	7.91
Shoplifting	223.21
Total	**269.29**

Boreham et al, 2006

5) The New English and Welsh Arrestee Drug Abuse Monitoring Programme (NEW ADAM)

The NEW-ADAM study comprised a rolling programme of research based on 16 locations, surveyed at two-yearly intervals. Arrestees were drug-tested and surveyed about their drug use and offending levels (over ten selected acquisitive offences – see below) over the past year. The self-reported offending was also compared to conviction data to check reliability. Across four sites for which results were reported, 28% of those arrested self-reported heroin use in the last year and 25% reported crack use. The full results of the self-reported offending are shown in Table A14 below:

Table A14: Offending data from NEW ADAM

	Used neither heroin or crack	Heroin Only	Crack/ Cocaine Only	Both	Total
Number of Arrestees	418	41	103	158	720
Mean Number of Acquisitive Offences in Past Year	52	114	104	206	97
Total Number of Acquisitive Offences in Past Year	21736	4674	10712	32548	69670
Percentage of Total	31.2%	6.7%	15.4%	46.7%	100.0%

Source: Bennett and Holloway, 2004

The report only gave breakdowns for individual crime types on a binary measure: the number who admitted to committing that offence or not in the previous year. These results are shown below:

Table A15: Numbers committing each offence, NEW ADAM

	Numbers Committing Each Offence			
	Used neither heroin or crack	Heroin Only	Crack/Cocaine Only	Both
Theft of vehicle	34	4	21	32
Theft from vehicle	31	5	12	30
Shoplifting	64	17	20	109
Dom Burglary	17	6	0	18
Commercial burglary	22	2	9	25
Robbery	3	2	5	8
Theft person	3	0	3	4
Fraud	29	3	17	34
Handling	78	16	35	73
Dealing	24	4	22	37
Total	305	59	144	370

Source: Bennett and Holloway, 2004

Note that summing the totals for these comes to more than the total number of individuals in the sample (720) because one individual can admit to more than one offence. To obtain an estimate for the number of offences committed by opiate or crack-cocaine users in each crime type, we make the assumption that the breakdown of volume of offences matches the breakdown from the binary measure.[147] This gives the results below:

[147] Obviously this is a big assumption, and is likely to mean that crimes like shop-lifting are under-counted and lower volume crimes like burglary may be over-counted. Ultimately this was the main reason we favour the Arrestee Survey estimate over NEW-ADAM in the final model.

Table A16: Final offending rates, NEW ADAM

	Numbers Committing Each Offence					
	Used neither heroin or crack	Heroin Only	Crack-Cocaine Only	Both	Total OCU	OCU Offending Rate
Theft of vehicle	2,423	317	1,562	2,815	4,694	15.54
Theft from vehicle	2,209	396	893	2,639	3,928	13.01
Shoplifting	4,561	1,347	1,488	9,588	12,423	41.14
Dom Burglary	1,212	475	0	1,583	2,059	6.82
Commercial burglary	1,568	158	670	2,199	3,027	10.02
Robbery	214	158	372	704	1,234	4.09
Theft person	214	0	223	352	575	1.90
Fraud	2,067	238	1,265	2,991	4,493	14.88
Handling	5,559	1,268	2,604	6,422	10,293	34.08
Dealing	1,710	317	1,637	3,255	5,208	17.25
Total	**21,736**	**4,674**	**10,712**	**32,548**	**47,934**	**158.72**
CSEW Total	**6,250**	**1,331**	**3,013**	**8,023**	**12,366**	**40.95**

Source: Bennett and Holloway, 2004

6) The Offending, Crime and Justice Survey (OCJS)

The Offending, Crime and Justice Survey (OCJS) was a nationally representative, self-reported offending survey that in 2003 asked 10,000 people aged 10 and over, who were resident in households in England and Wales, about their attitudes towards, and experiences of crime and drug use. (Roe & Ashe, 2008)

As with the Arrestee Survey, though the OCJS was nationally representative, a weighting system was used to compensate for greater non-response amongst certain groups. The weighting system ensured that there were representative proportions of males, females, juveniles and adults in the sample.

To decide whether respondents were OCUs, the following question was used:

- Use of heroin or crack cocaine 'Once or twice a week' or 'Most days'
- Use of heroin or crack cocaine 'Most days'

Again, we used the widest definition for the model so as not to apply a falsely high offending rate to a wider population than is justified. Adults arrested in the previous year were removed from the OCJS dataset in order to ensure that there was no overlap with the Arrestee Survey, as this could lead to double-counting. Hence the offending rates below refer only to OCUs who had *not* been arrested in the previous year.

The survey asked questions regarding prevalence and volume of offending in relation to the main acquisitive crime types, from which weighted, annual volumes were calculated and hence average annual rates per OCU. The weights ensured representativeness as explained above. The results are shown in Table A17 below:[148]

Table A17: OCJS annual offending rates for OCUs who do not get arrested

OCJS annual offending rates	
Domestic Burglary	0
Commercial Burglary	0
Theft of Vehicle	1.01
Theft from Vehicle	0.03
Theft from Person	0
Commercial robbery	0
Personal robbery	0
Other Theft	1.19
Violence	1.77
Criminal Damage	0
Shoplifting	0.54
Drug Supply	4.73
Total	**9.26**

Source: Roe and Ashe, 2008.

[148] The OCJS asked separately about attempted thefts but attempts are not covered in the Arrestee Survey so attempted vehicle thefts are not included in the calculations. This again means that the estimates here are conservative in by comparison with the CSEW which includes attempts as crimes.

Appendix 7: Assumption log for main model

Assumptions Relating to the OCU Trend			
Assumption	**Explanation/Evidence**	**Sensitivity Analysis**	**Suggested Further Work**
Starting number of new OCUs in 1975 = 2000	The Addicts Index records that there were 926 new heroin notifications in 1975, though we know this is likely to be an under-count. Prevalence estimates derived from the Addicts Index have used a multiplier of between 3 and 10 but incidence will have a smaller multiplier. We therefore use a multiplier of 2 for the model and round to the nearest 1000.	The Addicts Index Figure effectively provides a lower bound of around 1,000 and a it seems highly unlikely that in 1975 (pre-epidemic), the multiplier for incidence would have been greater than 3 so we run sensitivity analysis using 1000 and 3000 as 1975 incidence values. This has a very marginal effect on the main results.	Though the assumption is weak, it seems to only have a very marginal effect, so this area does not seem a priority for further work.
We assume that the distribution of the age of initiation remains constant throughout the period.	Two studies were located that had a distribution of age of initiation from two different time periods: Donmall et al use data from 2001-2003 and Millar et al use data from 1986-2000. The two distributions show a very high degree of consistency despite being from different periods. Also, many other studies from the relevant period, 1975-2013, record the mean/median age of initiation. (See for example Degenhardt et al, 2000; Johnson, 2001; Keen et al, 2000). In none of these studies was the average peak age of initiation outside the range of 17-22.	Due to the strength of the evidence underlying this assumption we have not conducted sensitivity analysis on this.	Certainly we would welcome further studies analysing whether the age distribution of initiation has changed in recent years.
Likewise we assume that the cessation rate is constant through the period. (Note, that we don't assume what that cessation rate is - this is derived from the trial and error process) but we do assume throughout that cessation rates don't change over time.	This is an assumption that reduces complexity but could be justifiably challenged. If, for example, treatment leads to higher rates of cessation, then the expansion of treatment services through the period would mean the cessation rate would change over time.	A dynamically varying cessation rate would be a very complicated thing to build into the model, so we have not been able to conduct sensitivity analysis on this. However, we note that if treatment has improved cessation rates in the recent period, this would be likely to make the results in relation to crime trends even more marked as it would heighten the decline in criminality in the recent period.	This is an important area for further work. A systematic review of the evidence on cessation rates and whether they have varied over time (and by area) would be very welcome.
We assume that a trial-and-error process gives an approximate of the best fit for the incidence trend, given a fixed cessation rate.	To try and eliminate any bias (conscious or sub-conscious) in the trial and error process, we had several different researchers (some connected to the project, others not) attempt trial and error for the different model runs. But it is possible that some bias remains.	To completely avoid any bias we set up an Excel solver function to calculate the incidence profile that produced the best fit against the scoring criteria in order to remove any human trial-and-error process. The results of this are shown in Appendix 9.	Not relevant for further work.
We assume that the two sources of evidence under-pinning the scoring process are correct. That is, we assume that the central estimates for OCUs provided by Hay et al are correct and we assume that the age distribution of the opiate/crack cohort on the DDW is representative of the entire cohort.	The Hay et al estimates have been challenged due to the capture/recapture methodology and the fact that they rely heavily on treatment sources hence may operate with a slight lag. However, they remain the best estimates we have for OCU prevalence in recent years and the DDW does provide a degree of corroboration for them, though the two are based on many of the same underlying sources.The extrapolation assumption for the DDW feels less problematic as we have data on around two-thirds of the cohort. It is possible that the missing third could have a markedly younger profile, though given this data applies to 2008, if there were a large cohort of hidden, younger users at this time it is likely these would have been visible in the treatment data in the more recent period (2010-13). Yet we have seen nothing like this. The youngest age groups have continued to decline at the fastest rates. (see Chapter 3).	To test the sensitivity of the model to the Hay et al assumptions, we perform model runs in which those estimates are 10% and 30% bigger/smaller respectively. The runs in which the Hay et al estimates are bigger make the crime impact of the epidemic stronger, increasing the estimates for the amount of the rise and fall that are due to opiate/crack use. The effect gets weaker for the runs in which the Hay et al estimates are reduced.	Further research is already being undertaken in this area (and others) as part of the Nationally Integrated Quantitative Understanding of Addiction Harm (NIQUAD) research project(s). One project, for example involves developing an alternate method for calculating OCU prevalence, that can be used to triangulate the Hay et al estimates. Some of the projects will also include more sophisticated models of the drug-crime link at the national level.
Though not exactly an assumption, the selection of the Hser-based 2 cessation rate profile for the final results could be challenged on the grounds that a) it is derived from a dated US study, b) the derivation itself involves some assumptions given we cannot be exactly sure from the data provided what the cessation rate is at each follow-up and c) other cessation profiles had just as good or even better scores.	We selected Hser-based2 because it achieved a very good model fit but also was more in keeping (we felt) with the evidence from studies like Kaya et al (2004), Sweeting et al (2009) etc which show a very high cessation rate in the early years of OCU careers. It is particularly important that the Sweeting study is UK-based and looks at data from the current period, which gives us some confidence that the Hser findings are applicable. The other cessation rate options that scored well (i.e. a fixed 5% cessation rate) seemed implausible for the early career years, given this evidence.	To test this assumption we ran the model with alternative cessation rates. The results are sensitive to the cessation rate - for example, using a constant 5% exit rate (including both cessation and death) reduces the proportion of the rise in acquisitive crime explained to 35-51% and the proportion of the fall explained to around 17%	As above - this is clearly an important area for further work. A systematic review of the evidence on cessation rates and whether they have varied over time (and by area) would be very welcome.

Assumptions Relating to Average Offending Rate(s)			
Assumption	**Explanation/Evidence**	**Sensitivity Analysis**	**Suggested Further Work**
For the estimates using an arrestee/non-arrestee split, we effectively assume that the Arrestee Survey offending rates are appropriate for any members of the OCU cohort who are post-initiation and who get arrested in that year. Likewise we assume that the OCJS offending rates are appropriate for those post-initiation who do not get arrested in the year.	Data from the DDW and Ball et al (1983) suggest that during periods of addiction (proxied by a positive drugs test in the DDW sample) offending rates are high regardless of age. The Arrestee Survey, given that it involves self-reported offending and drug use would seem to offer a reasonable source for estimating this rate, and it is corroborated by NEW-ADAM, which shows very similar rates in a different arrestee cohort. It is crucial to note that this assumption (coupled with the one below) does NOT mean the model assumes around 30% of OCUs continue to offend at this rate throughout their careers. Instead it merely assumes that in any given year, around 30% of users will be regular users who get arrested and those users will be offending at around the rate of the Arrestee Sample rate, for that year. The following year, the make-up of the 30% might be entirely different users. This seemed the best way to model the addiction/non-addiction variation evident in the literature.	To test the importance of the offending rates we re-ran the model increasing/decreasing all offending rates by 10% and 30%. As expected the results are sensitive to offending rates but not dramatically so. Even reducing offending rates by 30% and taking the treatment estimate (which generally gives more conservative results) would suggest that the epidemic explains just over a third of the rise in acquisitive crime and around 20% of the fall.	Arguably this is the most important area for further research. It is clear that offending rates by OCUs are dynamic and will vary considerably across careers. It's also clear that this variation is unlikely to be due only to age, but will also be affected (perhaps to a far greater degree) by different phases in the drug career: initiation, regular use, cessation, re-lapse etc. Yet we have little evidence from UK cohorts in these areas. The accuracy of the current estimates could no doubt be improved enormously if this work could be undertaken.
Linked to the assumption above is that we assume that the proportion of the cohort that gets arrested is constant (around 30%) and can be derived by looking at the number of arrestee OCUs in the Arrestee Survey as a percentage of the total OCU cohort from that year (taken from the Hay et al estimates).	Limitations of the Hay et al estimates have already been discussed. The only other assumption in the derivation of the single-year estimate for the proportion of regular users who get arrested in a given year is that there is no sampling bias in the Arrestee Survey, which seems like a reasonable assumption. The more problematic issue is assuming that this proportion is constant over time.	To see how sensitive the results were to this assumption we tried rates of arrestees among the OCU population of 40% and 20%. (i.e. Roughly ten percentage points either side of the central estimate). Obviously, this has no effect on the treatment-based estimates, but the arrestee-method estimates are quite sensitive to this assumption. For example, assuming just 20% of regular opiate/crack users get arrested in any given year reduces the amount of the rise in acquisitive crime explained by the model from 77% to 55% and the amount of the fall explained reduces from 33% to 24%.	As above - it is absolutely crucial to get more evidence on the dynamics of OCU offending over time.
For the estimates using the in/out of treatment split we effectively assume that the average pre-treatment offending rate from NTORS/DTORS/Coid et al is aplicable to anyone post initiation but not in treatment; and that the post-treatment offending rate from NTORS/DTORS/Coid et al is applicable to any OCU post initiation and in treatment.	There are a number of issues with this assumption. The most obvious is the time extrapolation. We are effectively extrapolating self-reported offending from a 4-week/6-month measure up to much longer periods. This would be incorrect if the period immediately prior to seeking treatment were not typical of all the periods of the OCU career in which an individual is not in treatment. To judge this - we have seen that, during periods of addiction (which we effectively proxy here by not being in treatment), aggregate offending rates are high regardless of age, and we have also presented self-report evidence to show that users themselves do not regard the period immediately prior to addiction as an especially chaotic period of offending. However, some studies do suggest this. Furthermore, it might be argued that this method will over-estimate the offending rate for individuals who manage to quit for periods mid-career without treatment (if they were to quit entirely they would drop out of the model so it is not an over-estimation in that sense). This is a fair challenge, but there is - perhaps - an equally fair one in the opposite direction. The arrestee offending rate estimates are far higher than those gleaned from the treatment studies (some of which excluded the most high-rate offenders), so it could be argued that the treatment results will underestimate offending. In this light it is worth pointing out that Anglin & Speckart found rates of offending prior to treatment that were four times greater than pre-initiation but that Ball et al (1983) found rates around six times greater consistently, during periods of addiction; hence pre-treatment rates may well be an under-estimate of the offending rates of OCUs during their most chaotic periods.	See section above on sensitivity analysis of offending rates.	As above - it is absolutely crucial to get more evidence on the dynamics of OCU offending over time.
We assume that an average of the three treatment studies provides the most accurate offending rate.	This feels a reasonable assumption given that there is quite a high degree of consistency across the studies, though each has its own methodological weaknesses (which we list in full in Chapter 6).	We tested the most logical alternative, weighting the studies by sample size, and this had a very marginal effect on the overall results.	It would be interesting to see if current OCU arrestees report similar rates of offending.
We assumed that the Arrestee Survey was a better measure of the arrested OCU offending rate than NEW ADAM.	The main reason for selecting the Arrestee Survey was that to match up the NEW-ADAM results with CSEW crime volumes would have involved another large assumption - that the New-Adam binary offending measure could be converted into volumes.	We repeated the results using NEW ADAM and this had a very marginal effect on the central results - it simply made the effect of the epidemic very slightly greater in the arrestee-method model.	It would certainly be useful to see if current OCU arrestees report similar rates of offending.
We assume that DTORS/NTORS/Coid et al capture the change in offending rates in and out of treatment	This is a subtle but important point. We are not - in the study, looking for the reduction in offending caused by treatment. We are looking for a proxy offending rate for those in treatment. This may be lower due to the treatment, but it may be lower for other reasons. Therefore we feel it is justified to use the post-treatment NTORS/DTORS/Coid et al results to capture this.	See above for sensitivity analysis on offending rates.	Though it is not central to this model, it is of course of importance generally to study the properly controlled effects of treatment, so we'd welcome any further work in this area.

Assumptions Relating to Average Offending Rate(s) - continued			
Assumption	**Explanation/Evidence**	**Sensitivity Analysis**	**Suggested Further Work**
To create the trend in % of OCUs in treatment we assume that: i) the NDTMS numbers are correct for the years in question (and implicitly that the Hay et al estimates are accurate figures for the total OCU population) ii) that the RDMD 6-month estimates for the period 1993-98 are accurate, and iii) that prior to 1993 the percentage of OCUs in treatment was constant.	Essentially we have better data on treatment numbers more recently, so these assumptions become less robust as we move back through time. However, they are also likely to impact the model less as we move back through time as any reasonable estimate of the percentage of OCUs in treatment through the 1980s and early 1990s would be quite low.	None undertaken.	We would welcome any evidence to improve these figures especially for the period prior to 2000.
We make a number of assumptions associated with matching crime types from individual studies to the categories in the CSEW. These are listed along with their justification in Chapter 6.	See Chapter 6 for more.	None undertaken.	There is a great deal of variation in the results of studies that have, for example, measured the split of OCU burglary offending between domestic and commerical burglary. So further work in this area would be welcomed.
For the counterfactual we assumed that 20% of all offending by OCUs would have occurred anyway.	The justification for this is set out in length in the counterfactual section in Chapter 6. Obviously we welcome comments and suggestions for improvement.	For sensitivity we tested alternative counterfactuals of 30% and 50%. As expected the results are reasonably sensitive to the counterfactual assumption - but again, not dramatically so. Even a 50% counterfactual still left the model finding that opiate/crack use explained 34-48% of the rise in acquisitive crime and 18-21% of the fall.	Clearly, developing a robust counterfactual for offending rates across an OCU career is certainly a research priority, and it may be that further examination of the DDW could help improve on our current estimates.
We assume that offender self-report is the most reliable method for capturing total crime committed by these individuals.	Numerous studies have looked at the viability of self-report with most concluding that it is reliable and preferable to criminal justice system data (see Farrington et al 2006; Manzoni, Parker etc). But admittedly - not everyone agrees, see for example Bukten et al, 2013.	None undertaken.	This issue remains not definitely resolved, so further work would be helpful.
By matching up offending rates from offender surveys up to the CSEW we effectively assume that crime volumes as reported by offenders are the same as crime volumes reported by victims.	It would seem likely that if anything, there may be a bias towards victims reporting a larger amount of crime than offenders, if for example offenders selectively forget or reduce the true volume of offending in their most chaotic periods. However, we have no hard evidence for this.	None undertaken.	This may well make for an interesting area of future study.

Appendix 8: The break in the Addicts Index data

The Addicts Index has data on new and total addicts (for drugs of all kinds), and a breakdown of these by drug type. This allows for the creation of the total and new heroin users series that we use throughout this report. But there was a break in the series for total addicts, and hence for total heroin users. Up to 1987, the total addicts series counted all new addicts notified plus any former addicts re-notified in that year except those who were in treatment at the beginning of the year. After 1987, the total addicts series counted new and former addicts as before, but also any individuals in treatment at the start of the year who were then re-notified during the year. This has the effect of inflating the numbers from that point on. The new addicts and the new heroin users trends do not have this break in the series. Two values for 1987 exist, one using the original method and one with the updated method to allow for comparison.

As an aside, this demonstrates another reason why the Addicts Index data is an under-count of reality. As well as the fact that many users will not seek medical help and therefore may not be notified at all, the counts pre-1987 will not include anyone who starts the year in treatment (as these were not seen as being former or new addicts). Even the period post-1987 is not a complete count of known users as anyone who starts the year in treatment and simply stays in treatment throughout the year, without being re-notified, would not (we think) have been counted.

Appendix 9: Alternative OCU trend results using excel solver

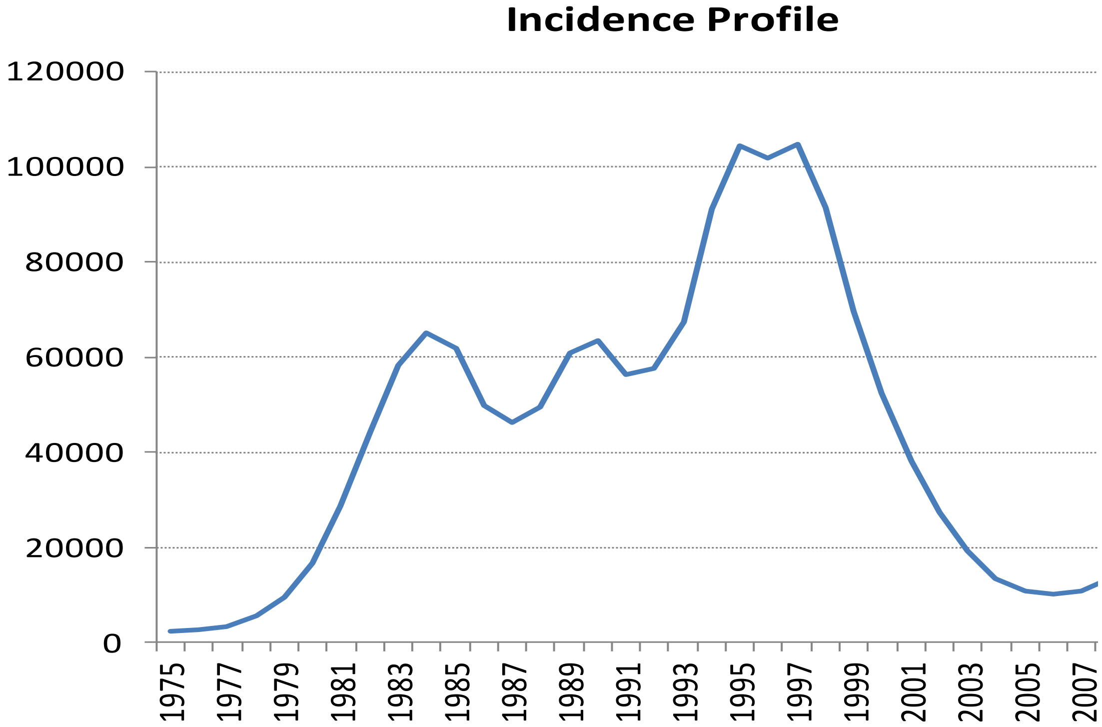
Excel solver is an optimisation tool that can maximise / minimise a target value by varying input cells subject to constraints that can be set by the user. In this case it was used as an alternative to the trial–and-error process outlined in Chapter 6. That is, it was used to minimise the difference between actual data on the current cohort of OCUs and the observed modelling results by varying the incidence rate: the number of new users of heroin/crack in each year from 1995 to 2012.

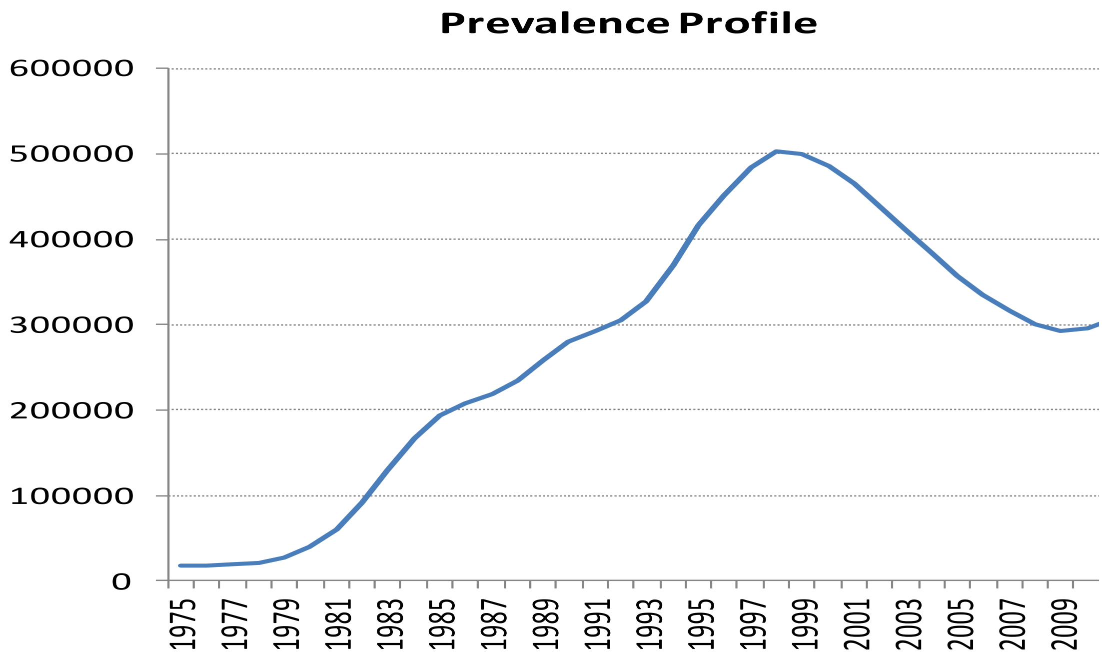
The exit rate used for this analysis was the Hser-Based 2 rate – the one used in the final model from Chapter 6. Excel solver was used to vary the incidence rate from 1975 to 2015 subject to the constraints below. These bounds have been set fairly loose whilst ensuring that solutions remain constrained to realistic values:

- The incidence rate could not increase by more than 80% nor decrease by more than 30% in any year.
- From 1975-1980 the year–on-year difference in incidence rate could not change by more than +- 50%.
- From 1981-2015 the year-on-year difference in incidence rate could not change by more than +- 15%.

The difference between the actual and observed results was reduced as far as possible. Consequently we were able to use the model to better understand the trends in the number of OCUs over time. The results for this are shown in the two graphs below. The first graph is the incidence profile for new OCUs and the second graph is the prevalence profile for the total population of OCUs.

Figure A1: OCU trends using excel solver rather than trial-and-error to determine the incidence profile





In general these results are not dramatically different from those reported in the main paper. The total number of opiate/crack users shows a 1998 peak which is within the range suggested by the trial-and-error results in Chapter 6.

The incidence profile is a bit different however. The solver results show a much clearer two-wave pattern in the incidence of opiate/crack use. That is, they suggest two very distinct periods of rapid increases in new users, one in the early 1980s and one in the early-to-mid 1990s. The solver results also suggest that incidence peaked between 1995 and 1997 which is slightly later than the results in the main paper, though the dramatic drop from 1998 onwards is consistent.

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