Drug-related crime

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Non-technical summary

Drug-related crime is estimated to account for a large part of the economic and social costs of illicit drug use and also to make up a large share of total crime. However, when measuring criminal activity it is extremely difficult to disentangle crime which is directly caused by drug use from crime that is linked to drug use but is caused by other factors. The distinction is important because, when evaluating the costs or benefits of drug policy reform, only crime which is caused by drug use should be considered. This study discusses this concept of drug-related crime, reviews methods for estimating it and produces estimates of drug-related crime in England and Wales in 2003-6.

We provide a critical discussion of the concept of drug-related crime, arguing that the relevant comparison is not between existing crime levels and those in a world without drugs, but between existing crime levels and those that would exist under plausible reforms to drug policy. We consider three illustrative policy scenarios: (i) a benchmark, but unrealistic, scenario in which drugs are unavailable; (ii) free supply of drugs to dependent users (e.g. supervised injection) that would avoid recourse to the illegal market; and (iii) the introduction of a regulated drug supply that changes market prices. We discuss how accurately standard comparison methods (using data on drug users and the criminal behaviour) measure drug-related crime under each scenario.

We then derive estimates of drug-related crime using four alternative comparison methods applied to survey data from England and Wales. To ensure full coverage of the population while including sufficient numbers of drug users and individuals who have committed crime, we combine the household-based *Offending Crime and Justice Survey* and the *Arrestee Survey* conducted in police arrest facilities. We focus on three groups: heroin users, cannabis users (not involved with heroin or cocaine) and cannabis suppliers.

We find three key results. First, the volume of drug-induced acquisitive crime linked to heroin use is high, at 160-230 offences a year for heroin users generally and 200-260 offences for heroin injectors. However, there is no significant evidence of violent crime linked directly to heroin use (although heroin suppliers may be involved in violent crime). Second, we find no evidence at all of any drug-induced crime committed by people who only use cannabis. Third, we find evidence that supplying cannabis (only) leads to a small volume of crime, amounting to 2.5-9 acquisitive offences and 0.9-2.7 violent offences on average per year. The mechanisms linking cannabis supply to criminal activity merit further investigation.

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Abstract: We provide a critical discussion of the concept drug-related crime and review methods for estimating its volume, emphasising the importance of an appropriately defined counterfactual. We then construct new estimates for England and Wales in 2003-6, combining data from the Arrestee Survey and Offending Crime and Justice Survey to ensure adequate coverage of prolific offenders/drug users and non-household residents, who are under-represented in household surveys. We find, first, that the volume of drug-induced acquisitive crime linked to heroin use is high, but there is no significant evidence of violent crime linked directly to heroin use. Second, we find no evidence at all of any drug-induced crime committed by people who use cannabis (but not heroin or cocaine). Third, we find evidence that supplying cannabis leads to a small volume of crime. The mechanisms linking cannabis supply to criminal activity merit further investigation.

1   Introduction

Drug-related crime undoubtedly accounts for a large part of the external costs of illicit drug use. For example, Godfrey et al (2002) estimated that around 88% of the economic and social costs of class A drug use in England and Wales in 2000 was attributable to crime and policing costs, while the UK Drug Harm Index (MacDonald et al. 2005, 2006), which attempts to measure the trend over time in drug-related social harms, assigns over two-thirds of its weight to property crime. For Australia in 2004/5, Collins and Lapsley (2008) estimate that 41-51% of crime was attributable to drug use and that crime was responsible for 56% of the tangible costs arising from illicit drugs in 2004/5. The ONDCP (2004) gives broadly similar estimates for the US.

A better term for the concept at issue here is drug-induced crime, since we are concerned with crime that is causally related to drug use. In a much-cited paper, Goldstein (1985) made a distinction between three types of drug-induced crime.[1] "Economic-compulsive" crime arises from a need for additional income to fund the drug purchases made necessary by compulsive drug use. "Psychopharmacological" crime is behaviour generated by the action of drugs on the brain, resulting in weakened self-control or decision-making capacity, or violent responses to external provocation. "Systemic" violence is seen as a feature of the working of illicit markets, where legal enforcement of contracts is impossible. Note that economic-compulsive crime may relate to any form of strongly-desired consumption, not only illicit drugs – some people may commit crime to generate money to buy alcohol, tobacco, clothes, etc. To these direct forms of drug-related crime, we could add long-run indirect effects which are hard to evaluate but may be important. For instance, if drug use impairs intellectual ability, educational achievement and employment prospects, acquisitive crime becomes more rewarding relative to legal income-generating activity and crime becomes a 'rational' response to lack of opportunity for some.

There is a large research literature on drug-related crime and some empirical associations are consistently observed (see Stevens et al 2005 for a survey), but the direction of causation is unclear, and crime is often found to precede drug use in individual offending careers (Hammersley et al 1989, Pudney 2003, D'Amico et al 2008, Hales et al 2009). Heroin use is associated with high rates of acquisitive but not violent crime (Hammersley et al 1989, Fischer et al 2001) but there is a weaker association between cannabis use and acquisitive crime, and research on the effects of cannabis on the brain does not suggest a link to violence (Hoaken and Stewart 2003). Systemic crime linked to the cannabis market may be particularly important in some particular instances, such as the recent gang violence in Mexico largely attributable to supply to the US marijuana market, and some episodes of human trafficking and exploitation linked to cannabis production in the UK. The few studies of other markets subject to exogenous

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[1] See Bennett and Holloway (2009) for a critique.

switches in legality suggest significant increases in systemic violent crime as a consequence of the banning of a previously legal market (see Miron 1999 on alcohol prohibition and Chimeli and Soares 2011 on the Brazilian mahogany trade).

Research is hampered by the difficulty of estimating the counterfactual level of crime that would have been committed by drug users or suppliers in the absence of drugs. The usual difficulty of establishing causality in a non-experimental setting is particularly important here because, as pointed out by Burr (1987), drug consumption and criminal activity are choices made by the individual. What does it mean to say that drug use causes crime, if they are joint outcomes of the same choice? This question, addressed in sections 2.1-2.4 below, is often neglected in the applied literature and in the statistical literature on causal inference.

2   Concepts and methods

In 1998, the United Nations General Assembly Special Session (UNGASS) adopted the slogan "*A drug free world - we can do it!*", and the conceptually loose definition of drug-related crime which implicitly underpins most attempts at measurement reflects this:

Definition*:* The volume of drug-related crime is the difference between the volume of crime in the world as it is and the volume of crime that would exist in an otherwise identical world with illicit drugs unavailable.

This is not a helpful definition, for at least two reasons. First, despite the UNGASS display of confidence, a drug-free world is completely implausible and other policy-related counterfactuals are of more practical interest. In practice, we are interested in some change in the policy regime which may alter (but not reduce to zero) the level of drug use. A second problem with the definition is that the nature of the counterfactual is likely to depend on the means by which it is achieved. A world with drugs eliminated by a perfectly successful programme of interdiction and incarceration of drug traffickers would look very different from a world with drugs eliminated by a successful public information and education campaign.

Liberalisation of cannabis supply and the provision of clinics for supervised injection of prescribed heroin are two examples of counterfactuals that arise in current policy debates. They are useful examples, because they involve drug-induced crime in conceptually different ways, as discussed in sections 2.3-2.4. However, no modern country has yet pursued supply liberalisation to the full extent of legalisation and there have only been small local experiments with supervised heroin injection, which we review in section 8 below.

We first consider the conceptual basis for measurement under the UNGASS counterfactual, and then examine the issues involved in moving to more realistic policy-related counterfactuals. Given the uncertainties involved in measurement, it is unreasonable to expect a single fully

defensible estimate of the volume of drug-induced crime. Instead, our strategy is to use a number of different survey-based approaches to indicate the range of plausible estimates, and then compare these estimates with the effects identified by the few experimental studies that exist. Our data are summarised in section 3 and implementation of the methods in section 4. Results are presented in sections 5-7 and compared to existing experimental evidence in section 8. The implications of our findings for the social cost of drug use are considered in section 9.

2.1   Concepts of drug-induced crime

There are conceptual difficulties arising from the fact that drug use is a choice rather than a 'treatment'. We use an illustrative single-period choice theory of drug demand which, although too simple to be a full description of demand behaviour, captures the nature of the measurement problem. It also emphasises an important point often overlooked in the medical literature: that drug users – however 'addicted' they may be – are consumers and respond to economic incentives in much the same way as the consumers of other goods.

Assume a single illicit drug h with market price p. Criminal activity yields disutility rather than consumption benefits but can be used as income-generating activity. Individuals behave in accordance with the following utility maximisation programme:

$$\max_{h,q,c \geq 0} U(h,q,c) \tag{1}$$

subject to:

$$ph + q \leq b + \pi c \tag{2}$$

where q is expenditure on legal consumption goods, c is criminal activity, $U(.)$ is increasing in h and q and decreasing in c, π is the rate of return to crime and b is legal income. The programme (1)-(2) has solutions for drug use and crime $\tilde{h}_1(p,\pi,b)$ and $\tilde{c}_1(p,\pi,b)$ which divide individuals into two groups: drug users, for whom $\tilde{h}_1 > 0$, and non-users, for whom $\tilde{h}_1 = 0$.

Now impose the counterfactual intervention as a further restriction $h = 0$, assuming no general-equilibrium effects causing b and π to change. The new outcome is $\tilde{h}_2 = 0, \tilde{c}_2(\pi, b)$, where $\tilde{c}_2 = \tilde{c}_1$ if $\tilde{h}_1 = 0$, since non-users are unaffected by withdrawal of drug supply. The impact on the criminal behaviour of those who are drug users under the status quo is $\tilde{c}_1 - \tilde{c}_2$, which is the "average effect of treatment on the treated" (ATT) in the language of causal inference. That terminology is inexact here, because drug use is choice rather than treatment and the "non-treated" are only unaffected because of the nature of their choices. For that reason, we refer to the impact as a pseudo-ATT (PATT), defined as:

$$\text{PATT} = \text{E}\big(\tilde{c}_1 - \tilde{c}_2 | \tilde{h}_1 > 0\big) \tag{3}$$

The aggregate per capita volume of drug-induced crime is then the product of the PATT and the drug prevalence rate. None of the usual methods for estimating the volume of drug-related crime

provides a direct estimate of the PATT. We consider four approaches:

(*i*) *Naive assumption.* If drug users would, in the absence of drugs, be crime-free, then $\tilde{c}_2 = 0$:

$$\text{PATT}_1 = \text{E}(\tilde{c}_1 | \tilde{h}_1 > 0) \tag{4}$$

This is an implausible assumption, yielding an upper bound on the volume of drug-induced crime, given the empirical fact that drug use is very often preceded in the development process by other forms of illegal behaviour (Hales et al 2009, Pudney 2003). Nevertheless, it underpins much discussion of drugs policy: for example, it is assumed by Godfrey et al (2002) and is implicit in the construction of the UK Drug Harm Index (MacDonald et al 2005, 2006).

(*ii*) *Exogenous selection into drug use.* We could assume more reasonably that, without drugs, people who are currently users would, on average, have committed the same level of crime as non-drug users, so that $\text{E}(\tilde{c}_2 | \tilde{h}_1 > 0) = \text{E}(\tilde{c}_1 | \tilde{h}_1 = 0)$:

$$\text{PATT}_2 = \text{E}(\tilde{c}_1 | \tilde{h}_1 > 0) - \text{E}(\tilde{c}_1 | \tilde{h}_1 = 0) \tag{5}$$

(*iv*) *Matching.* The measure (5) ignores the fact that drug users tend to have different characteristics and personal histories than non-users, and it can be improved by using a reference group of better-matched non-users to construct the counterfactual. This can be done using propensity score matching (Rosenbaum and Rubin 1983) or Mahalanobis matching (Rubin 1980, Abadie and Imbens 2006). It requires further information on a set of characteristics x describing the individual and his or her personal history, such that the post-intervention criminal activity of a drug user with characteristics x is, on average, the same as that of a non-user with the same characteristics, so that $\text{E}(\tilde{c}_2 | \tilde{h}_1 > 0, x) = \text{E}(\tilde{c}_1 | \tilde{h}_1 = 0, x)$:

$$\text{PATT}_3 = \text{E}(\tilde{c}_1 | \tilde{h}_1 > 0, x) - \text{E}(\tilde{c}_1 | \tilde{h}_1 = 0, x) \tag{6}$$

(*iii*) *Self-assessed motivation.* A fourth approach, pursued for the US by ONDCP (2004) and for Australia by Collins and Lapsley (2008), is to use drug users' own assessments, *m*, of the amount of their own criminal activity which is induced by their drug use. This embodies the assumption that $\text{E}(m | \tilde{h}_1 > 0) = \text{E}(\tilde{c}_1 - \tilde{c}_2 | \tilde{h}_1 > 0)$ and, consequently:

$$\text{PATT}_4 = \text{E}(m | \tilde{h}_1 > 0) \tag{7}$$

This too is open to objection on grounds that criminals themselves may be no better at analysing causation than are social researchers and may find it convenient to blame an external factor for their own behaviour, leading to overestimation of the volume of drug-induced crime.

2.2 Theoretical validity of comparison methods

The literature on causal inference is dominated by the concept of 'treatment', although methods are often applied in contexts where choice, rather than treatment is involved, with little

discussion of the relationship between choice theory and matching methods. None of the four measures (4)-(7) follows directly from choice theory and, in particular, it is not at all obvious that the measures PATT_2 and PATT_3, based on comparisons between groups of users and non-users, are consistent with the principles of choice theory. After all, if users and non-users were entirely comparable, there would be no distinction between the two – either everyone would be a user or everyone a non-user. So we must allow for the possibility of factors that induce some to use drugs, while others do not. A separability assumption gives these comparison methods some theoretical validity. Assume the utility function is:

$$U = u(v(h, q, c; x), h; x, z) \tag{8}$$

where the component functions $u(.; x, z)$ and $v(.; x)$ are common to all individuals and (x, z) is the complete set of personal characteristics, history and circumstances which determine the form of preferences with respect to crime, drug use and general consumption. Note that z is critical here, since it is responsible for the distinction between drug users and non-users within the set of people with any particular set of characteristics x.

Suppose – implausibly – that a successful interdiction policy causes the constraint $h = 0$ to be imposed directly. Crime is then determined by maximisation of the sub-utility function $v(q, c; x)$ subject to the budget constraint $q \leq b + \pi c$ and is therefore unaffected by the subset of characteristics z which only influence crime-consumption choices when the optimal choice involves drug use. In this model, a drug user with characteristics (x, z) will, under the drug-free counterfactual, have crime level identical to that of a non-user who shares the relevant subset of characteristics, x, so that $\text{E}(\tilde{c}_2 | \tilde{h}_1 > 0) = \text{E}(\tilde{c}_1 | \tilde{h}_1 = 0)$ and, provided that x is used to perform the matching, the measure PATT_3 is valid. Without the separability assumption (8), matching on x alone is invalid, since z acts as an unobserved confounder. On the other hand, if we were to attempt matching on both x and z, all individuals would have the same drug use status, so one of the 'treatment' and 'control' groups would be empty, and matching would be impossible. The exclusion of z from the consumption-crime subutility means that there exist personal factors which could predispose the individual to drug use but would not also predispose him/her to a high crime-high consumption lifestyle. It is possible that genetic variations in brain function recently identified by neuroscience may fit this role (Mayer and Höllt 2005). The separability assumption (8) is not unduly restrictive: it allows for Goldstein's (1985) economic-compulsive pathway via the budget constraint and also the psychopharmacological pathway since variation in h may change the marginal rate of substitution between consumption and crime.

Extension of the analysis to more realistic counterfactuals than the hypothetical disappearance of illicit drug supply may require further assumptions for the validity of user-nonuser comparisons. We consider two types examples of intervention: supervised heroin injection for

addicts; and licensing and regulation of the drug market.

2.3 Other counterfactuals: supervised injection facilities

Consider a policy that makes available to dependent drug users a free supply $\bar{h}$, used under supervision. With this intervention in place, there is still access to an illegal drugs market, allowing participants to raise consumption above the maintenance level $\bar{h}$ by a positive amount $d = h - \bar{h}$ if desired. Supervision means that prescribed drugs cannot be sold to generate income and, assuming the satiation level is above $\bar{h}$, utility maximisation is equivalent to:

$$\max_{d \geq 0, c \geq 0} u\left(v(\bar{h} + d, b + \pi c - pd, c; x), \bar{h} + d; x, z\right) \qquad (10)$$

At a corner solution with no resort to the black market, (10) reduces to maximisation of $v(\bar{h}, b + \pi c, c; x)$, rather than $v(0, b + \pi c, c; x)$ which is maximised by non-users. Consequently, $E(\tilde{c}_2 | \tilde{h}_1 > 0) \neq E(\tilde{c}_1 | \tilde{h}_1 = 0)$ and PATT$_3$ is not a reliable guide to the impact of the intervention.

To avoid this problem, we need to make a stronger separability assumption under which preferences are representable by the utility function

$$U = u(v(q, c; x), h; x, z) \qquad (11)$$

This implies that the marginal rate of substitution between general consumption and criminal activity is independent of drug use, ruling out Goldstein's (1985) psychopharmacological causal mechanism. Under (11), criminal activity chosen by a drug-using criminal is a function only of the returns to crime and residual income remaining after paying for drugs. This structure embodies a definite restriction on the pattern of behaviour but, in the absence of compelling evidence for the pharmacological mechanism, it is credible as a basis for measurement.

In this case, drug-users operating at a corner solution and non-users both maximise the same function $v(q, c; x) = v(b + \pi c, c; x)$, so PATT$_3$ is valid. However, the matched control group of non-users only works perfectly if the drug maintenance level $\bar{h}$ is high enough to prevent all resort to the illicit market. A drug user operating at an interior solution above the prescribed dose $\bar{h}$ maximises $v(b + \pi c - pd, c; x)$, which differs from the objective of a non-user. Consequently, even under this stronger form of separability, we would expect the matching technique to underestimate the volume of crime in the counterfactual environment, since purchase of black market drugs is likely to be accompanied by additional criminal activity, and thus over-estimate the potential crime reduction that induced by the intervention.

2.4 Other counterfactuals: liberalisation of supply

Now consider the case of liberalisation of drug supply and assume that the principal effect of the policy change is to reduce the market price p. To derive a direct relationship between the effect

of this intervention and the PATT, we need to use the full separability assumption (11), implying that the crime function for a drug-user with characteristics (x, z) is:

$$\tilde{c} = f(\pi, y; x) \tag{12}$$

where $y = b - p\tilde{h}(p, \pi, b; x, z)$ is residual income after drug costs. If policy produces a marginal change, dp, in the drug price, the impact on crime committed by this drug user is:

$$d\tilde{c} = -\tilde{h}[\partial f / \partial y][1 + \epsilon]dp \tag{13}$$

where ϵ is the price elasticity of demand for drugs. The pseudo-Engel coefficient $\partial f / \partial y$ is expected to be negative since high income reduces the incentive for crime. Note first that, if the drug has a price elasticity of -1, the impact on crime is zero, despite the rise in volume of drug consumption. It is the drug expenditure response to the price change that matters for acquisitive crime, not the quantity response. Only if drug demand is inelastic ($-1 < \epsilon < 0$) will the impact on crime be positive. There are few convincing estimates of the price elasticity of heroin but, for cannabis, several studies suggest a price elasticity around -0.5 (Clements and Zhao 2005, Van Ours and Williams 2005). If this is true for drug h, the percentage change in crime caused by a 1% price rise will be $d\tilde{c}/\tilde{c} = -0.5p\tilde{h}(\partial\tilde{c}/\partial y)/100\tilde{c}$, which is expected to be positive. Consequently, rising drug prices increase, rather than reduce, the volume of crime. While drug 'droughts' caused by interdiction actions may succeed in reducing consumption and internal harm to the health of users (Day et al 2003), by raising prices they may also have the perverse effect of increasing external social harm from drug use. This raises the issue of distributional equity between drug users and the non-user community.

The PATT measures the impact on crime of a removal of drug supply. To convert this into a measure of the impact of a price change, multiply by the impact on drug use of a price change dp. The appropriate way to do this is in proportionate expenditure terms, giving: PATT $\times$ $d(p\tilde{h})/(p\tilde{h}) =$ PATT $\times (1 + \epsilon) \times dp/p$. This gives the correct measure (13) if PATT $= -p\tilde{h}(\partial f / \partial y)$, which holds as a tangent approximation since, by the mean value theorem:

$$\text{PATT} = \text{E}\left(f(\pi, b - p\tilde{h}; x) - f(\pi, b; x)\right) = [\partial f / \partial y^*][-p\tilde{h}] \tag{14}$$

for some point y^* in the interval $[b - p\tilde{h}, b]$. This approximation is good if crime choices are approximately linear in residual income or if drug expenditure is small. If crime is a decreasing convex function of residual income, use of the PATT will tend to overstate the true impact on crime. Note that, if PATT is zero, then the impact of a policy-induced price change on drug-related crime is unambiguously zero.

3   UK survey data

Conventional household-based surveys are poor vehicles for measurement of illegal activity.

Prolific offenders and drug users have low survey response rates and some lead disordered lives which exclude them from standard sampling frames. To improve coverage of groups with high rates of drug use and criminal activity, we need a complementary survey with better focus on this group. Since we need to compare the criminal activity of drug-users and non-drug-users, data from the monitoring records of drug treatment programmes, such as NTORS and DTORS (Jones et al 2007, 2009), are not suitable, since their samples are conditioned on the existence of some form of drug dependence. Surveys which select individuals on a crime-related basis (for example through arrest or imprisonment) are potentially more useful, since they include both drug users and non-users. All surveys targeted at groups with high prevalence of crime and drug use involve selection problems, since they are inherently representative only of a small, partly self-selected part of the population. Unfortunately there are no current British surveys that have the required coverage of both criminal activity and drug use. However, during 2003-6, there were two such surveys focused on the general household and arrestee populations. Our solution to the coverage problem is to combine both datasets in a composite analysis using the household-based *Offending Crime and Justice Survey* (OCJS) and the *Arrestee Survey* (AS), conducted in police arrest facilities. Both surveys relate to England and Wales in the period 2003-6 and carry detailed questions about drug use and offending behaviour.

3.1 The Arrestee Survey

The 2003-6 AS was a short-lived annual cross-section survey of arrestees in police custody, used to monitor the prevalence of problem drug use and unmet need for drug treatment among the offender population, and as a basis for investigating the relationship between drug use and crime. The target population for the AS is the population of people aged 17 and over arrested on suspicion of committing an offence. For people arrested multiple times, re-interview within the survey year was avoided. The sample itself was designed to be representative of the population of arrest events flowing through police custody suites above a minimum size thresholds (containing at least one interview room and processing at least 2,000 arrests a year). The absence of an advance sampling frame for arrestees renders conventional sample designs infeasible, so the AS instead randomised the timing and location of interviewer shifts, and interviewers were required to attempt interviews with all arrestees in custody during the shift. A stratified random sample of 72 police custody suites was used and, because arrestees are difficult to contact after release, interviews were conducted while respondents were in police custody, using computer-assisted personal interviewing (CAPI) and, for the sensitive subjects of crime and drug use, computer-assisted self-interviewing (CASI). Saliva screening tests were also used to detect biological evidence of recent drug use. The use of survey weights is particularly important for the AS, and weights are used to adjust for three possible sources of non-

representativeness: (*i*) the oversampling of larger custody suites where cost per interview is low; (*ii*) non-response, caused by a number of process-related factors as well as refusals; (*iii*) the higher sample inclusion probability of prolific offenders. Further details of questionnaire content, survey design and construction of weights are given in Boreham et al (2006).

3.2   The Offending Crime and Justice Survey

The OCJS is a survey of individuals aged 10-65, living in private households in England and Wales. Sampling was from the Postcode Address File, using a 2-stage design with postcode districts as primary sampling units. The survey was conducted in four waves over 2003-6 as a panel in which a sub-sample of 10-25 years olds were followed from year to year, and supplemented by a further booster sample of 10-25 years olds each year. Weights are available for the full sample to adjust for the effects of sample design, attrition and nonresponse. Interviewing was done using a combination of CAPI and CASI and covered a range of issues including detailed descriptions of offending behaviour and drug use and experience of arrest and other contact with the criminal justice system. The arrest information is particularly important for our purposes, because it allows us to identify the overlap between the arrestee population and the household population, which we exploit in constructing a composite estimate for the whole population (see section 7 below).

3.3   Empirical definitions

Implementation of the alternative estimation methods set out above requires appropriate definitions of a drug user and measures of criminal activity. We use five alternative definitions of drug-users and non-users: heroin injectors; heroin users; arrestees who give a positive screening test for opiates; cannabis users and cannabis suppliers. All five are available in the AS, while the OCJS includes very few reports of heroin use and injection and does not use bio-assay and thus omits the third completely. The last two measures compare cannabis users (suppliers) who are not currently using (supplying) hard drugs with others who are using (supplying) neither. The definitions all use to a "last month" reference period, to focus only on current users.

 We use four measures of criminal activity, all adjusted to relate to a 12-month reference period: the number of episodes of shop theft; the total number of acquisitive crimes; total net proceeds from acquisitive crime; and the number of violent crimes. We use offence counts from both the AS and OCJS, but we do not use the proceeds of crime in the OCJS analysis because these items were only collected for a maximum six offences; thus they will understate the proceeds of crime for the most frequent offenders. Crimes directly involved in the workings of the drug market itself (possession, production, trafficking, etc.) are not included in these definitions, although they may be an important source of income for some drug users. Tables A1 and A2 in the

appendix set out the definitions and summary statistics for our measures of drug use and crime for the AS and OCJS non-arrestee samples respectively.

5 Single-sample estimates

The empirical association between drug use and crime in the AS and OCJS samples are summarised in Table 1, which shows the average volume of crime committed by those classed in various ways as people currently involved with drugs. This is the naïve estimate of average drug-related crime $\hat{\Delta}_1$, which assumes a crime-free counterfactual for each drug user. In the AS, heroin users commit an average of around 200 shop crimes a year, a further hundred or so other acquisitive crimes, generating illegal income of around £10,000 a year, or £30 per crime episode; and they report that around half of these crimes are causally related to their drug use. The average arrestee who uses cannabis only, commits around 27 acquisitive crimes a year, yielding a little over £1,000 of illegal income, very little of which is attributed to drug use. Arrestees involved in the supply of (only) cannabis are intermediate between heroin and cannabis users. On average, they commit about half as much acquisitive crime as a heroin user, generating about half the level of income, and they report that a quarter to a third of their offending is caused by their drug use. They report more than double the number of violent offences than the average heroin user.

The OCJS can only identify three of these categories: heroin users, cannabis-only users and suppliers of cannabis (or other non-class A drugs) who do not also supply class A drugs. Again, heroin users commit more crimes in general than cannabis-only users, although the comparison is subject to considerable uncertainty because there are very few heroin users in the sample. They report committing on average around 1.5 acquisitive crimes a year, compared to about 0.3 crimes among cannabis-only users. Suppliers of 'soft' (non-class A) drugs commit more crime than cannabis users but less than heroin users, with the exception (as in the AS) that non-class A suppliers appear to commit more than double the number of violent crimes than either of the other two groups. Overall crime levels among non-arrestees are, as we would expect, much lower than in the AS, for example cannabis-only user commit on average 0.3 acquisitive crimes a year, compared to 27 crimes among cannabis-only users who were arrested.

Table 1 Empirical associations between drug use and crime ($\hat{\Delta}_1$)

	Heroin injector	Heroin user	Positive opiates test	Cannabis-only user	Cannabis-only supplier
Arrestee Survey [1]					
Number of shop thefts	209 (12.4)	221 (13.5)	179 (13.9)	12 (1.6)	71 (13.4)
Number of acquisitive crimes	320 (15.3)	335 (16.8)	261 (17.4)	27 (2.9)	173 (28.2)
Net proceeds of acquisitive crime	£10,015 (751)	£10,581 (737)	£9,344 (898)	£1,153 (209)	£5,493 (1,082)
Number of violent crimes	2.4 (0.4)	3.5 (0.9)	1.5 (0.2)	2.4 (0.3)	10.9 (2.2)
% of crimes committed to buy drugs	43.3 (2.3)	46.1 (2.3)	35.6 (2.3)	5.0 (0.9)	23.9 (4.2)
% of crimes committed whilst high or to buy drugs	49.8 (2.1)	52.4 (2.2)	40.1 (2.4)	9.3 (1.1)	34.6 (4.8)
Offending, Crime and Justice Survey [2]					
Number of shop thefts	-	1.05 (0.53)	-	0.18 (0.05)	0.44 (0.17)
Number of acquisitive crimes	-	1.53 (0.71)	-	0.33 (0.06)	1.10 (0.33)
Number of violent crimes	-	0.44 (0.28)	-	0.85 (0.12)	1.87 (0.40)

[1] Means calculated using weights adjusting for sample design, non-response and arrest frequency. [2] Means calculated using weights adjusting for sample design and non-response. Standard errors in parentheses, calculated allowing for stratified and clustered sample design.

5.1   Estimates under exogenous selection

Table 2 gives results for the estimate $\hat{\Delta}_2$, based on the more realistic assumption 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. Comparison with corresponding figures from Table 1 shows a modest reduction in estimated levels of drug-related crime. For heroin users, the estimated volume and proceeds of drug-related crime fall by up to 13% when the zero-crime counterfactual is abandoned, while the estimate of the volume of violent crime falls by 20-80% (but note that statistical precision is low). For cannabis-only users and suppliers, the estimate of drug-related acquisitive crime is reduced by a quarter to a third, with a much larger reduction for violent crime by cannabis-only users.

Table 2 Estimated drug-induced crime among arrestees: exogenous selection ($\hat{\Delta}_2$)

Crime measure	Indicator of drug use				
	Heroin injector	Heroin user	Positive opiates test	Cannabis-only user	Cannabis-only supplier
Arrestee Survey [1]					
Annual number of shop thefts	197 (12.2)	213 (13.3)	167 (13.9)	8.4 (1.8)	46.1 (13.5)
Annual number of acquisitive crimes	296 (15.2)	315 (16.8)	234 (17.4)	19.1 (3.0)	131 (29.1)
Annual income from acquisitive crime	£8,878 (741)	£9,697 (730)	£8,334 (887)	£774 (222)	£4,081 (1,090)
Annual number of violent crimes	0.48 (0.45)	1.70 (0.94)	-0.62 (0.40)	1.57 (0.29)	9.61 (2.26)
Offending, Crime and Justice Survey [2]					
Annual number of shop thefts	-	1.01 (0.53)	-	0.17 (0.05)	0.41 (0.17)
Annual number of acquisitive crimes	-	1.45 (0.71)	-	0.30 (0.06)	1.04 (0.33)
Annual number of violent crimes	-	0.09 (0.28)	-	0.57 (0.13)	1.54 (0.40)

[1] Means calculated using weights adjusting for sample design, non-response and arrest frequency. [2] Means calculated using weights adjusting for sample design and non-response. Standard errors in parentheses, calculated allowing for stratified and clustered sample design.

5.2   Estimates with individual matching

The aim of matching methods is to compare drug-using arrestees with non-users who are matched as closely as possible in terms of personal characteristics which represent the individual's predisposition to criminal activity. Since 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. For this reason, we choose variables which, as far as possible, reflect fundamental risk factors specific to the individual. A constraint on the choice of matching variables is the requirement for there to be no direct causal impact of current drug use on those variables. Consequently, we use variables which pre-date current drug use; they are summarised in Appendix Table A3.

We use two variants of the estimator, one which matches individuals by minimising the distance between their observed characteristics, measured by the Mahalanobis quadratic distance measure (Rubin 1980), the other minimising distance measured by the propensity score (Rosenbaum and Rubin 1983). In both implementations, matching is carried out separately for males and females and the overall estimate constructed as the appropriate weighted mean. Each

member of the drug-user ('treatment') group is matched to the two closest members of the non-drug ('control') group. The results, summarised in Table 3 (AS) and Table 4 (OCJS), are not very sensitive to the way the method is implemented, nor to variations in the set of variables used for matching. Matching has the effect of reducing estimates of the volume and proceeds of acquisitive crime commited by heroin users by 4-17%. Estimates of crime committed by cannabis users are greatly reduced and become insignificantly different from zero. Estimates of crime linked to cannabis supply are reduced by 20-45% for the arrestee sample and somewhat less for the OCJS when matching is used, but the estimated volumes remain significant for all crime categories for the AS and for violent offences for the OCJS.

Table 3 Estimated drug-induced crime among arrestees ($\hat{\Delta}_4$)

Crime measure	Indicator of drug use				
	Heroin injector	Heroin user	Positive opiates test	Cannabis-only user	Cannabis-only supplier
Mahalanobis matching					
Annual number of shop thefts	176 (11.7)	199 (10.7)	140 (12.1)	-1.55 (3.87)	26.7 (20.4)
Annual number of acquisitive crimes	253 (14.6)	282 (13.4)	195 (15.0)	3.22 (5.09)	89.5 (27.2)
Annual income from acquisitive crime	£6,284 (914)	£8,348 (812)	£7,398 (827)	-£132 (449)	£4,010 (1,356)
Annual number of violent crimes	-1.77 (0.91)	0.28 (0.70)	-2.33 (0.53)	0.00 (0.70)	7.68 (2.39)
Propensity score matching					
Annual number of shop thefts	178 (11.1)	205 (10.6)	144 (11.5)	2.19 (3.44)	7.05 (17.9)
Annual number of acquisitive crimes	255 (13.9)	291 (12.9)	194 (14.2)	4.50 (5.03)	80.7 (25.2)
Annual income from acquisitive crime	£7,465 (798)	£8,105 (799)	£6,782 (838)	-£41.6 (369)	£3,434 (1,451)
Annual number of violent crimes	-0.26 (0.60)	0.68 (0.66)	-1.46 (0.61)	0.75 (0.56)	7.71 (2.23)

Standard errors in parentheses.

Table 4 Estimated drug-induced crime among the household population ($\hat{\Delta}_4$)

	Indicator of drug use		
	Heroin user	Cannabis-only user	Cannabis-only supplier
Mahalanobis matching			
Annual number of shop thefts	1.12 (1.34)	0.15 (0.12)	0.35 (0.38)
Annual number of acquisitive crimes	1.67 (1.54)	0.26 (0.13)	0.91 (0.51)
Annual number of violent crimes	0.12 (0.34)	0.29 (0.24)	1.44 (0.56)
Propensity score matching			
Annual number of shop thefts	1.21 (1.34)	0.15 (0.11)	0.36 (0.38)
Annual number of acquisitive crimes	1.81 (1.54)	0.24 (0.13)	0.85 (0.52)
Annual number of violent crimes	-0.43 (0.47)	0.34 (0.24)	1.42 (0.56)

Standard errors in parentheses.

5.3 Self-assessed motivation for crime

The AS contains two questions on the motivation for crime: one asks for the proportion of the respondent's crimes that he or she has committed in order to pay for drugs; another asks for the proportion of crimes committed whilst 'high' on drugs. Answers are categorical: "all", "most", "some" or "none"; and, for quantitative analysis, we assume these equate to average proportions 100%, 67%, 33% and 0% respectively. The results are presented in Table 4 below. In most cases, they are slightly smaller than the estimates of drug-induced crime produced by matching methods in the AS sample (Table 3). Both suggest a lower level of drug-induced crime than the naive estimates in Table 1 or Table 2. For heroin users, these estimates indicate that around three-quarters of their acquisitive crime is attributable to drug use, but virtually none of their violent crime. For cannabis users, a negligible (and mostly statistically insignificant) volume of crime is attributed to drug use by the matching and self-assessment methods.

Table 5 Estimated drug-induced crime among arrestees: self-assessed motives ($\hat{\Delta}_3$)

Crime measure	Indicator of drug use				
	Heroin injector	Heroin user	Positive opiates test	Cannabis-only user	Cannabis-only supplier
Crimes committed to buy drugs					
Annual number of shop thefts	158 (20.2)	174 (22.5)	140 (25.7)	3.63 (1.10)	32.8 (8.5)
Annual number of acquisitive crimes	224 (24.2)	245 (26.8)	197 (29.1)	10.5 (5.82)	96.1 (46.0)
Annual income from acquisitive crime	£7,162 (1,130)	£7,809 (1,222)	£7,007 (1,700)	£131 (33.7)	£1,881 (678)
Annual number of violent crimes	1.43 (0.58)	1.55 (0.64)	0.47 (0.13)	0.40 (0.13)	3.73 (1.16)
Crimes committed under the influence of drugs or to buy drugs					
Annual number of shop thefts	160 (19.6)	176 (21.8)	142 (25.6)	4.19 (1.11)	35.6 (8.49)
Annual number of acquisitive crimes	228 (23.3)	250 (25.7)	201 (28.8)	11.8 (11.1)	106 (44.9)
Annual income from acquisitive crime	£7,298 (1,142)	£7,943 (1,234)	£7,088 (1,695)	£160 (37.2)	£2,085 (671)
Annual number of violent crimes	1.54 (0.58)	1.64 (0.63)	0.58 (0.14)	0.50 (0.14)	4.47 (1.21)

6 Combined estimates

No one source of survey data is adequate for our purposes, and there are two alternative ways of combining multiple datasets. One is to concatenate the OCJS and AS samples (using weights to achieve the correct sample proportions) and then carry out estimation on the merged sample. Another is to implement the estimates separately for the OCJS and AS samples and combine the results. Under ideal conditions, the former approach is preferable, since the latter entails some negative bias, essentially because an arrestee can never be matched to a non-offending non-arrestee within the AS. But the ideal merged-survey approach only works if the appropriate set of matching variables is observable in both the OCJS and AS surveys, and this is not the case in practice. Differences in questionnaire content mean that merging the samples would only allow matching on a reduced set of characteristics and it is doubtful whether this could adequately

deal with the confounding problem, leading to a substantial over-estimate of the true causal impact of drug-use on crime. For this reason, we combine separate PATT estimates, but we first consider the potential bias entailed and give an indication of its likely magnitude.

Consider a simple matching framework in which we estimate a PATT defined as:

$$\Delta = E_x\{E(c_1|d = 1, x) - E(c_0|d = 0, x)\} \qquad (15)$$

where c_0 and c_1 are the crime levels that would be observed with drug use absent or present and the outer expectation is with respect to the distribution of x in the drug-involved population. Separating arrestees ($a = 1$) and non-arrestees ($a = 0$), the PATT can be written:

$$\Delta = E_x\{E(c_1|d = 1, x, a = 1)P(a = 1|d = 1, x) + E(c_1|d = 1, x, a = 0)P(a = 0|d = 1, x)\}$$

$$-E_x\{E(c_0|d = 0, x, a = 1)Pr(a = 1|d = 0, x) + E(c_0|d = 0, x, a = 0)Pr(a = 0|d = 0, x)\}$$

which can be re-expressed as:

$$\Delta = \Delta(a = 1)P(a = 1|d = 1) + \Delta(a = 0)P(a = 0|d = 1) + E_x\{A(x)B(x)\} \qquad (16)$$

where $\Delta(a) = E_x\{w(a, x)[E(c_1|d = 1, x, a) - E(c_0|d = 0, x, a)]\}$ is the weighted PATT conditional on arrest status, using weights $w(a, x) = P(a|d = 1, x)/P(a|d = 1)$, which adjust for differences in the risk of arrest.

Equation (16) implies that the true PATT is a weighted combination of separate PATT constructs for arrestees and non-arrestees, plus a bias term which is the expected value of the product of two components: $A(x) = Pr(a = 1|d = 1, x) - Pr(a = 1|d = 0, x)$ and $B(x) = E(c_0|d = 0, x, a = 1) - Ec_0|d = 0, x, a = 0$. These are respectively the difference in the probability of arrest for drug-users and non-users and in the expected crime level for drug-free arrestees and non-arrestees. Both are positive so combining separate PATT estimates from the OCJS and AS will underestimate the scale of drug-induced crime to some degree.

We do not have a full set of covariates x observable in both surveys, so the bias term cannot be estimated exactly; nevertheless, there is some indication of the typical size of these terms. OCJS estimates of the mean unconditional difference $Pr(a = 1|d = 1) - Pr(a = 1|d = 0)$ are 0.078 for heroin use, 0.026 for cannabis use and 0.005 for cannabis supply.[2] Estimates of the mean difference $E(c_0|d = 0, a = 1) - E(c_0|d = 0, a = 0)$ from AS and OCJS data are respectively 19.20, 8.34 and 42. 38 for the number of acquisitive crimes and 1.4, 0.6 and 0.9 for the number of violent crimes.[3] Multiplying these together,[4] indicates a downward bias in the estimated annual mean level of drug-induced crime of around 2 acquisitive crimes and 0.2 violent crimes for

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[2] Standard errors 0.055, 0.005 and 0.009 respectively
[3] Standard errors 1.29, 1.26 and 2.76 (acquisitive crimes) and 0.17, 0.19, 0.14 (violent crimes).
[4] Note that $E(AB) = \text{cov}(A, B) + (EA)(EB)$, so we are assuming that the covariance over x of A and B is small.

heroin use; 0.2 acquisitive and 0.02 violent crimes for cannabis use; and 0.4 acquisitive and 0.01 violent crimes for cannabis supply. Given all the other estimation uncertainties, this does not seem a cause for particular concern.

Without further information, the AS and OCJS are not sufficient because they do not tell us the relative sizes of the household and non-household or arrestee and non-arrestee populations, and they do not cover the non-arrestee, non-household population. We solve this coverage problem with a mixture of assumption and further data. Population estimates from the Office for National Statistics give an estimate of the relative size of the household and non-household populations, but there is no available source of data on the non-arrestee, non-household population. Let $PATT_A$ and $PATT_{H,NA}$ be the PATT estimates from the AS and non-arrestee subsample of the OCJS data, respectively, giving the appropriate weighted average:

$$PATT = PATT_A \times P(a = 1|d = 1) + PATT_{H,NA} \times P(H, a = 0|d = 1)$$

$$+PATT_{NH,NA} \times P(NH, a = 0|d = 1) \qquad (17)$$

where $P(a = 1|d = 1)$, $P(H, a = 0|d = 1)$ and $P(NH, a = 0|d = 1)$ are the population proportions of arrestees, of non-arrestees in the household sector and of non-arrestees in the non-household sector, all conditional on drug use $(d = 1)$. The PATT for the last of these groups is not identifiable. If we assume a uniform PATT for non-arrestees in the household and non-household populations, $PATT_{NH,NA} = PATT_{H,NA}$, definition (17) simplifies to:

$$PATT = PATT_A \times P(a = 1|d = 1) + PATT_{H,NA} \times [1 - P(a = 1|d = 1)] \qquad (18)$$

and we then need only to know the population proportion of drug users who are arrestees, $P(a = 1|d = 1)$. Using the law of conditional probability, this is:

$$\frac{P(d = 1|a = 1)P(a = 1)}{P(a = 0, d = 1|NH)P(NH) + P(d = 1|a = 1)P(a = 1) + P(a = 0, d = 1|H)P(H)} \qquad (19)$$

The AS, OCJS and ONS population statistics identify $P(d = 1|a = 1)$, $P(a = 0, d = 1|H)$ and $P(H)$ respectively. The arrest probability $P(a = 1)$ is $P(a = 1|H)P(H)/P(H|a = 1)$, whose three components are identified by the OCJS, ONS and AS data respectively. The only term in (19) which is not identified is the first term in the denominator, $P(a = 0, d = 1|NH)$, which requires evidence on non-arrestee members of the non-household population. This term makes a small contribution to (19) since $P(NH)$ is small, and it can be neglected with little loss of accuracy. We assume that the proportion of drug-using non-arrestees is similar in the household and non-

household populations,[5] so that we can write P($a = 0, d = 1$|NH) ≈ P($a = 0, d = 1$|H) and the resulting approximation to the weight P($a = 1|d = 1$) is:

$$P(a = 1|d = 1) = \frac{P(d = 1|a = 1)P(a = 1|H)P(H)}{P(d = 1|a = 1)P(a = 1|H)P(H) + P(a = 0, d = 1|H)P(H|A)} \qquad (20)$$

Table 6 shows the components of the calculation of P($a = 1|d = 1$) for four of the definitions of drug status (note that bio-assay is not available for OCJS respondents). It is striking that the probability of arrest conditional on drug status varies widely across forms of involvement with drugs and that, for the two definitions of heroin user, it is so much higher than the arrest probability in the general population.

Table 6 Population proportions

Parameter	Estimate (%)	Standard error
Arrestee Survey: P(H | $a = 1$)	91.4	(0.40)
Population statistics: P(H)	94.1	(-)
OCJS: P($a = 1$ | H)	1.07	(0.08)
Combined: P($a = 1$)	1.09	(0.25)*
P($a = 1|d$ = heroin injector)	90.5	(4.76)*
P($a = 1| d$ = heroin user)	65.6	(7.42)*
P($a = 1| d$ = cannabis user)	4.99	(1.08)*
P($a = 1| d$ = cannabis supplier)	6.14	(1.48)*

* Calculated using an assumed value of 0.2 for the standard error for P(H)

Table 7 shows the resulting estimates of the mean level of drug-related crime for people aged 17 and over in England and Wales, with one of four forms of involvement with drugs. They are based on the propensity score estimates for the AS and OCJS samples and the weights reported in Table 8, for three categories of acquisitive crime and for violent crime. For the criminal income category, where no estimate is available for the OCJS, we have assumed average proceeds of £30 per acquisitive crime for the non-arrestee population. The overall results are below those estimated for the arrestee sample, because the rate of offending is so much lower in the non-arrestee population. For acquisitive crime committed by self-reported heroin users, they are about two-thirds the level reported by heroin-using arrestees alone; the difference is much smaller for heroin injectors, who are almost absent from the OCJS sample. Drug-related

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[5] The report of the National Equality Panel (NEP 2010) suggests that there are currently around 0.85-0.9m members of the non-household population, of whom over half are in residential care homes and therefore very unlikely to be illicit drug users. The next largest group is people in armed forces accommodation (0.22m), which seems unlikely to have an especially high rate of drug use and non-arrest. In fact, the weight (22) is not very sensitive to the unknown factor P($a = 0, d = 1$|NH), which would have to be considerably larger than P($a = 0, d = 1$|H) to make a significant difference to the calculation.

crime is estimated to be essentially zero among cannabis-only users as one might expect, and it is very small for cannabis-only suppliers, generating proceeds of around £5 per week.

Table 7 Combined-data estimates of the PATT

Crime measure	Indicator of drug use			
	Heroin injector	Heroin user	Cannabis-only user	Cannabis-only supplier
Annual number of shop thefts	161 (13.1)	135 (16.6)	0.25 (0.20)	0.77 (1.30)
Annual number of acquisitive crimes	231 (17.5)	191 (23.1)	0.45 (0.28)	5.75 (2.00)
Annual income from acquisitive crime	£6,760 (805)	£5,334 (795)	£4.77 (18.8)	£235 (102)
Annual number of violent crimes	-0.23 (0.55)	0.30 (0.47)	0.36 (0.23)	1.81 (0.55)

Note: Calculated using weights adjusting for sample design, non-response and arrest frequency. Standard errors in parentheses, calculated allowing for stratified and clustered sample design where possible.

7   Consistency with experimental evidence

There is no possibility of a direct controlled experiment involving the permanent removal of illicit drug availability, but there have been many experiments that evaluate interventions intended to reduce consumption of illegally-supplied drugs. Most of these experiments involve either the prescription of substitute drugs (primarily methadone) or direct prescription of opiates (usually injectable heroin or morphine). Substitutes are generally provided at little or no cost and can therefore be expected to reduce the demand for "street" drugs and consequently reduce the need for income-generating crime. These experiments are all conducted within the context of a drug treatment programme, so the effect of access to low-cost, high-quality heroin is necessarily confounded with the impact of the associated treatment. For this reason, we generally observe reductions in illicit drug use in the control groups that receive no heroin, as well as the treatment groups that do. This confounding makes it difficult to identify drug-induced crime directly from the experimental evidence.

Table 8 summarises recent experiments from six different countries, involving supervised injection of heroin for treatment-resistant drug users. As pointed out in a recent Cochrane review (Ferri et al 2006) and Rowntree survey (Stimpson and Metrebian 2003), these studies are not fully comparable in terms of observed outcomes and treatments. From a social welfare perspective, there are particular weaknesses in terms of their measurement of criminal activity as an outcome and their short durations. The experiments all provided randomly-selected

subsets of participants with high-quality injectable heroin in (average) doses ranging from 275mg to 548mg per day at zero or greatly reduced cost (but subject to the additional costs of attending the experimental site). The experiments were all driven by medical concerns and the published findings generally provide little information about the economic circumstances of the subjects or the net relative costs that they faced for 'street' and prescribed heroin.

All experiments recorded the observed impact on various outcomes, but particularly on health indicators and continued use of illicit heroin (measured through self report and/or biomarkers). Impacts were inferred either from comparisons of post-treatment levels in the treatment and control groups ("differences-in-levels") or by comparing differences between pre- and post-treatment outcomes for the control and treatment groups ("differences-in-differences").

The theoretical analysis of section 2.3 suggests that matching methods tend to overestimate the impact on crime of a heroin prescription programme that is not able to prevent all resort to the illicit market. All the experiments summarised in Table 10 reported large falls in the use of street heroin, ranging from 66% (Spain) to 85% (Germany) in terms of days use per month; abstinence rates rose from zero at baseline to 33% (Geneva) or 37/51% (England), the latter depending on measure used. These findings confirm what we would expect from basic consumer theory: that the provision of fixed supplies of a commodity at a zero or subsidised price will reduce the consumption of a close substitute (street heroin). Nevertheless, use of street heroin remained significant in almost all experiments, underlining the need for caution in applying external estimates of drug-related crime to projected interventions of this kind.

There is evidence of a reduction in acquisitive crime accompanying the reductions in the cost of heroin consumption brought about by the experiments, but it is hard to draw firm conclusions about the magnitude of the effect. There is little consistency in the recording and analysis of crime outcomes across the studies and those that do report impacts on the volume of criminal activity suggest an effect ranging from 44% (Canada) to 99% (Spain), although the substantial decreases observed also in the control groups suggest that much of this may be due to other aspects of the treatment programme. Our survey-based estimates suggest that around 75% of property crime committed by heroin users is drug-related. The experimental evidence certainly spans this figure, but the wide range of results prevents any firm conclusion being reached.

There are two major issues to bear in mind when comparing survey and experimental estimates. First, our analysis rests on a combination of OCJS and AS samples, with forms of random sampling used within their target populations and weighting used to adjust for selection into those populations. In contrast, convenience sampling is the primary method for recruiting experimental participants, who are screened in various ways. Past treatment failures and cooperation with an intensive treatment programme are requirements of participation and no

adjustment is made for refusal and other forms of non-response. These selection processes result in experimental groups with quite different characteristics than those of drug users generally – indeed, that is a deliberate feature of their design. Second, the effect of the accompanying psychosocial treatment (counselling, education, etc) in the experimental cases may modify the response that would be induced by the provision of low-cost heroin alone. We would expect treatment to amplify the tendency for crime to be reduced by the heroin intervention, so the true figure is somewhere below the total reported difference between baseline and end-of-treatment levels of criminal activity.

To summarise, we can say that, given the wide range of experimental estimates and the uncertainties involved in comparing survey-based and experimental estimates, there is no demonstrable inconsistency between the survey and experimental evidence on the extent of drug-induced crime.

Table 8 Evidence from European heroin injection experiments

Time and place	Intervention	Pre- and post-treatment illicit drug use	Crime outcome measure	Effect size
Switzerland (Uchtenhagen et al 1999): 15 cities, 1994-6	1035 heroin addicts in treatment, assigned to various experimental treatments mostly without randomised controls. 18 months duration. Some patients were required to pay a contribution to programme costs.	81% prevalence of daily illicit heroin use pre-treatment → 6% after 18 months. Significant decrease also for cocaine consumption but not cannabis.	(i) Court convictions (ii) Police-recorded offences (iii) Self-reported offences (iv) % income from illegal sources	$\Rightarrow$ 80% decrease $\Rightarrow$ 70% decrease in no. of offences $\Rightarrow$ 60% decrease in prevalence $\Rightarrow$ fall from 69% to 10%
Switzerland (Perneger et al 1998): Geneva 1995-6	51 heroin addicts in poor health with at least two past treatment failures, recruited in outpatient clinic. Treatment group received average of 480 mg intravenous heroin per day for 6 months and were required to give up driving. Control group received various other treatments, mainly methadone maintenance.	*Treatment group*: 100% daily street heroin use pre-treatment → 4% daily / 19% occasional use post-treatment\n\n*Control group*: 90% daily / 10% occasional pre-treatment → 48%, 19% post-treatment	(i) Pre-post treatment difference in criminal charges for acquisitive crime (ii) Pre-post treatment difference in criminal charges for violent crime (iii) Pre-post treatment difference in income from non-drug illicit income	$\Rightarrow$ -86% and +50% for treatment and control groups\n\n$\Rightarrow$ -67%, 0% for treatment and control groups\n\n$\Rightarrow$ -65%, +70% for treatment and control groups
Netherlands (van den Brink et al 2003, Dijkgraaf et al 2005): 6 cities: 1998-2000	549 heroin addicts participating unsuccessfully in methadone maintenance programmes (339 full compliers). 5 treatment groups received combinations of methadone and inhalable or injectable heroin (mean dose 548mg per day, within a maximum of 1000mg)	Not reported	(i) Mean days property crime during year (ii) Mean prosecutions for property crime / prostitution during year (iii) Mean prosecutions for violent crime	$\Rightarrow$ -61% difference-in-levels (10.3 v 37.5 days) $\Rightarrow$ -43% difference-in-levels (0.45 v 0.79 prosecutions) $\Rightarrow$ -88% difference-in-levels (0.02 v 0.16 prosecutions)
Germany (Haasen et al 2007): 7 cities, 2002-3	1015 heroin users with poor response to current treatment or who were not in treatment for at least 6 months. Comparison of 8 randomised groups differing in medication (injected heroin/oral methadone) and psychosocial care (education/case management). Study duration was 12 months (mean daily heroin dose 442mg)	Fall in use of illicit heroin: 85% (23 → 3 days per month), 65% (23 → 8 days) for treatment and control groups. Difference-in-levels for prevalence of positive urine tests for street heroin at 12 months: 18% (treatment), 30% (control). All figures approximate.	Not reported	

Table 8 continued

Time and place	Intervention	Pre- and post-treatment illicit drug use	Crime outcome measure	Effect size
Spain (March et al 2006): Granada, 2003-4	62 opioid-dependent subjects (44 full compliers) recruited in drug-dealing areas and through treatment contacts. All had 2 or more failed past spells of methadone treatment. Control group received methadone only; treatment group methadone + twice-daily injected heroin (average 275 mg. per day) and methadone (43mg.). All had access to social, legal, psychiatric & medical support. 9 month duration.	Use of street heroin fell by 66% (24.5→8.3 mean days per month) for the treatment group; and by 27% (23.3→16.9 days) for the control group.	Difference in mean no. of days' illegal activity in last month at baseline and at 9 months	99% decrease (11.5→0.6 days) for treatment group; 49% decrease (8.0→4.1 days) for control group
Canada (Oviedo-Joekes et al 2009): Montreal and Vancouver, 2005-8	226 heroin injectors with at least two past treatment failures. Control group received oral methadone (average dose 96mg.). The treatment group received injectable heroin (average daily dose 392mg.). Both groups also received psychosocial and primary care services. 12 months study duration.	No. days illicit heroin last month fell by 80% (26.6 → 5.3) for treatment group; 56% (27.4 → 12.0) for control group. Reductions in median spending were 73% ($1,200→$320 p.m.) for treatment group and 67% ($1,200→$400) for control group. No change in illicit cocaine use.	(i) Proportion with reduction in non-drug crime over treatment period (ii) Pre-/post-treatment difference in mean EuroASI subscale for illegal activities	⇒ 44% (treatment group); 34% (control group) ⇒ -46% (treatment group); -34% (control group)
UK (Lintzeris et al 2006; Strang et al 2010):Brighton, Darlington, London, 2005-8	127 long-term heroin injectors with continuing use of illicit heroin despite at least 6 months' oral methadone treatement. Treatment groups received (A) oral+injected methadone or (B) injected heroin+oral methadone. Control group (C) received oral methadone.	*Urine tests*: 37% of heroin group B, 18% (group A), 8% (group C) tested negative for street heroin in weeks 23-26. *Self report*: 51% (B), 19% (A), 17% (C) reported abstinence from street heroin.	Not reported	

8 The social cost of drug-induced crime

Crime involves a number of distinct costs and benefits to different parties. For example, a domestic burglary imposes a cost on the victim including the value of the goods lost and the cost of making good any damage caused by entry. Some of those losses may be met by household insurance, but there is a cost in acquiring that insurance cover and negotiating the claim. There may be further intangible costs in the form of psychological distress, which may persist in the form of an increased future fear of crime. Society as a whole bears a cost in the form of the policing and criminal justice response to the crime and possibly also health care costs if the burglary involved psychological or physical injury to the victim which prompted a response from the health care system. Society also bears some additional intangible costs from the social malaise that is caused by crime, particularly in certain neighbourhoods. Property crime also involves a transfer of resources. The criminal benefits from the income he or she gains from reselling the stolen property or using any stolen property that is retained. The dealer who handles the stolen goods profits from the transaction and the ultimate purchaser benefits from the opportunity to buy low-cost goods. These transfer benefits are almost never included in social cost accounting of crime, which normally rests on an unstated assumption that theft is pure economic loss, equivalent to total destruction of the stolen property.

It is difficult to put values on all these cost-benefit elements, even for financial costs, since the reporting or recording of the financial value of crime by victims (in surveys like the British Crime Survey), by criminals (in surveys like the OCJS and AS), and by agencies like the police and insurance companies are subject to wide margins of error, which are themselves not easy to estimate. However, some estimates do exist and we exploit these to construct a variable to represent at least part of the social cost of the crime reported by respondents to the AS and OCJS, which allows us to repeat the analysis of section 5 in social cost terms. The cost assumptions underlying construction of this variable are set out in Table 9. They are based, as far as possible, on the semi-official analysis by Dubourg et al (2005), which updates and improves upon the earlier costings of Brand and Price (2000). However, the more recent cost estimates only apply to crime against private individuals and households and excludes losses to commercial organisations. We therefore use a combination of the two sources. Table 11 also shows the cost estimates used by the official Drug Harm Index (MacDonald et al 2005). The estimates from Dubourg et al (2005) includes tangible costs ('defensive expenditures', insurance administration, value of property stolen or damaged, lost output, health and other services to victims, and policing and criminal justice costs) and also intangible costs (physical and emotional impact on the direct victims). The last category of costs is extremely important, since it makes up about half of the total social cost of crime against personal sector victims, but is

particularly difficult to value, with alternative methodological approaches giving widely differing results (Dolan et al 2005). The Dubourg et al estimates of intangible costs are based on quality-adjusted life years (QALYs), as used extensively in the evaluation of health interventions. To emphasise the large uncertainties involved in these cost estimates, Table 9 gives the unit costs we adopt for our calculations in rounded form to avoid spurious precision and we also give our own subjective indication of the range of uncertainty associated with them. They should not be interpreted as confidence intervals, since they reflect conceptual ambiguity at least as much as statistical error. Note also that there is some mismatch between the crime categories of Table 9 and those used in our analysis of AS and OCJS data. For example, the 'semi-licit' categories of begging and prostitution are excluded from Table 9 and thus are implicitly assumed to entail social costs equal to those of the average acquisitive crime.

Table 9 Assumed unit social costs of crime (2003 prices)

Crime category	Central estimate of unit cost	Range of uncertainty	Sources		
			BP2000[a]	DHT2005[b]	DHI2005[c]
Shop theft	110	80-140	110		70.54
Other non-vehicle theft	634	434-834	-	634	375
Theft of vehicle	5000	4500-5500	—— 4924 [d]——		5900
Theft from vehicle	850	600-1000	—— 848 [d] ——		568
Domestic burglary	3250	2750-3750	-	3268	2535
Non-domestic burglary	3000	2500-3500	2976	-	2976
Personal robbery	7250	6750-7750	-	7282	5180
Shop robbery	5500	4500-6500	5511	-	-
Fraud	1600	1000-2200	1653	-	-
Personal robbery	7250	6750-7750	-	7282	5180
Shop robbery	5500	5000-6000	5511	-	-
Assault & wounding	3120	2600-3640	-	1440 / 8852 [e]	-

Notes: Gross external costs (£ per offence in 2003 prices), including tangible and intangible costs to victims and tangible costs to society in general (*not* net of benefit to criminals). [a] Brand and Price (2000) [b] Dubourg et al (2005) [c] Drug harm Index: MacDonald et al (2005) [d] Composite of/from theft of private vehicles (DHT2005) and commercial vehicles (BP2000) [e] Common assault and wounding, respectively.

We attach a social cost to estimates of drug-related crime by applying the average unit cost figures for acquisitive and violent crime to the PATT estimates in Table 7 for each category of drug user. Note that the acquisitive and violent crime categories overlap, because personal and shop robbery is common to both, so it is not strictly possible to sum them to obtain an aggregate figure for acquisitive and violent crime. The results are presented in Table 10, with indicative

ranges of uncertainty, constructed by combining the sampling error confidence intervals from Table 7 with the subjective uncertainty indicators from Table 9 by treating the latter as if they were normal 90% intervals. Although the arithmetic of confidence intervals is used to construct the ranges of uncertainty quoted in Table 10, they should be interpreted as largely subjective.

Table 10   Estimated per capita external social cost of drug-related crime

Crime measure	Indicator of drug use			
	Heroin injector	Heroin user	Cannabis-only user	Cannabis-only supplier
Acquisitive crime per user	85.3 [68.5 , 102.1]	80.0 [60.7 , 99.3]	0.3 [-0.01 , 0.6]	3.9 [1.6 , 6.2]
Violent crime per user	-1.6 [-8.1 , 4.8]	2.1 [-3.4 , 7.6]	2.6 [-0.1 , 5.3]	12.8 [6.3 , 19.2]
Group size ('000)	53.8 (35.0 , 72.6)	76.9 (55.3 , 98.5)	2,467 (2,342 , 2,592)	212 (177 , 247)
Aggregate social cost: acquisitive crime (£bn)	4.587 [2.437 , 6.737]	6.153 [3.585 , 8.720]	0.747 [-0.024 , 1.518]	0.829 [0.318 , 1.341]
Aggregate social cost: violent crime (£bn)	-0.088 [-0.438 , 0.261]	0.164 [-0.262 , 0.591]	6.346 [-0.345 , 13.04]	2.710 [1.273 , 4.148]

Note: Ranges of uncertainty in square brackets are indicative only and should not be interpreted as conventional confidence intervals.

The estimated social cost of drug-related crime caused by heroin use is high, probably in the range £65,000-100,000 per user. There is no detectable external cost in terms of crime imposed on society by those who use cannabis alone, but cannabis dealing appears to bring with it a significant level of mainly violent crime in the range £6,000-£20,000 per head, the greater part of which is in the form of assault of various kinds, rather than property-motivated robbery.

We estimate the size of each group of drug users as $N\,\mathrm{P}(d=1|a=1)\mathrm{P}(a=1)/\mathrm{P}(a=1|d=1)$, where N is the size of the England and Wales 17-65 population. Table 12 gives estimates of these numbers and the implied aggregate social costs, together with indicative ranges of uncertainty. The results suggest that the external social costs of acquisitive crime caused by current heroin use among the adult population in England and Wales amount to £3.6-8.7bn, of which £2.4-6.7bn is attributable to heroin injectors. Although there is a large point estimate for the aggregate social cost of violent crime caused by cannabis use, this is due to the large size of this group and the very high unit social cost assigned to violent crime. In fact there is no statistically significant evidence of any crime induced by cannabis use, which is reflected in the huge range of uncertainty spanning zero. A modest aggregate social cost of drug-related acquisitive (£0.3-1.3bn) and violent crime (£1.3-4.1bn) is attributed to cannabis suppliers. To put these figures in perspective, the NHS disease costs associated with tobacco smoking in England in 2006 have

been variously estimated as £2.7bn (Callum et al 2011) and £5.2bn (Allender et al 2009) and in Wales in 2007/8 as £0.39bn (Phillips and Bloodworth 2009).

9   Conclusions

We have focused particularly on three groups of people who are of particular interest in terms of drugs policy: (*i*) heroin users, because of the possibly high external cost their drug use imposes on society; (*ii*) users of cannabis who are not currently involved with heroin or cocaine, because of the high prevalence of cannabis consumption; and (*iii*) people involved in the supply of cannabis (only), because of their possibly high risk of transition into hard drug supply. Our aim was to estimate the magnitude of one component of the external social cost of drug use for these three groups – the additional property crime and violent crime which is causally linked to their involvement with illicit drugs. There are five main conclusions.

First, we find that the volume of drug-induced property crime linked to heroin use is high, but there is no significant evidence of violent crime linked directly to heroin use (this is not to say that there is no violent crime caused by heroin suppliers). The average level of acquisitive crime is probably in the range of 160-230 offences a year for heroin users generally, and rather more for heroin injectors (200-260 offences). Around 70% of these offences are episodes of shop theft. This criminal activity generates an income for the users estimated to be £4,000-6,700 a year (£5,500-8,000 for injectors). The cost imposed on society by heroin users' drug-induced crime is extremely high if we include an allowance for the distress as well as tangible losses experienced by victims and for the costs of reactive policing and criminal justice procedures. These social costs are highly uncertain, but we suggest that the annual social cost caused by an average heroin user is in the range £60,000-100,000, implying an aggregate cost from all (adult) heroin users in England and Wales in the range £3.5-10.5bn. There is no obvious conflict between these estimates and the results of various national heroin-injection experiments which have had the effect of greatly reducing resort to the market for expensive street heroin.

A second important finding is that there is no evidence at all of any drug-induced crime committed by people who use cannabis alone. This contradicts perceptions held by many of the general public: in a survey carried out by the Advisory Council on the Misuse of Drugs (2008, Table 6), two-thirds of those interviewed "tended to agree" or "strongly agreed" with assertions that cannabis use contributes to social disorder or to an increase in criminal activity.

Third, we find evidence of only a small volume of crime causally related to the activity of people involved in supplying (only) cannabis. This amounts to 2.5-9 acquisitive offences and 0.9-2.7 violent offences on average per year, with associated external social cost of £1,700-£6,400 (acquisitive) or £6,400-£19,300 (violent). Violent crime is sometimes a feature of drug supply so the latter result is unsurprising, but the interpretation of the finding on acquisitive crime is not

clear. Drug supply is often a source of income for drug users, so cannabis dealing could substitute for acquisitive crime rather than increase it. One possibility is that cannabis supply is acting here as a proxy for a particularly intensive level of cannabis use, which might be funded by a mixture of property crime and dealing activity. This merits further investigation.

A fourth conclusion relates to the available evidence base. Quantitative research on drug-related crime should be based on survey evidence that adequately represents population groups with high rates of offending and drugs use, and which makes it possible to address the difficult problems involved in identifying causal relationships. The ideal source of evidence would be a large-scale longitudinal survey representative of both the household and non-household resident populations. No such survey exists or is ever likely to exist, and we have used instead a composite multi-survey cross-section approach using matched comparison methods to estimate causal links. This was only possible because we have a targeted survey (the *Arrestee Survey*) of offending and drug use which covers both drug-using and non-drug-using offenders, and a general-population survey (the *Offending Crime and Justice Survey*) which also covers both offending and drug use. Both surveys were ended by the Home Office in 2006 and, to the best of our knowledge, there currently exist no surveys for England and Wales that would allow an updated analysis of this kind to be undertaken. Current Home Office surveys fail to cover both offending and drug use (for example, the *British Crime Survey* does not ask about respondents' own criminal activity, and the DTORS/NTORS treatment cohorts select only drug users and therefore offer no comparison with non-users).

The study is also significant on a theoretical and methodological level. We have shown that, in a context where both the 'treatment' and its 'outcome' are the result of individual choice, there is a link between the validity of statistical methods based on matching 'treatment' and 'control' cases and the assumption of separable preferences, giving a new rationale for the use of matching methods in settings where causality is a particularly difficult issue. We have also extended matching methods to settings which require a combination of endogenously-selected data sources to achieve adequate population coverage.

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Appendix: further tables

Table A1   Measures of drug use and crime: Arrestee Survey 2003-6

Indicator	Definitions	Sample nos. of users and non-users	Sample prevalence (%)
Heroin injector	*Users*: self-reporting both injecting drugs and heroin use in last month *Non-users*: all with valid responses to injecting and heroin questions	19,545	13.0
Heroin user	*Users*: self-reporting heroin use in last month *Non-users*: all with valid responses to heroin questions	18,998	13.4
Positive screening test for opiates	*Users*: positive saliva screening test result for heroin or morphine *Non-users*: all providing testable saliva sample	14,174	15.5
Cannabis-only user	*Users*: self-reporting use of cannabis but no use of heroin, cocaine, crack or methadone in the last month *Non-users*: all with valid responses to drug questions, who report no use of heroin, cocaine, crack or methadone in the last month	12,744	32.8
Cannabis-only supplier	*Users*: self-reporting selling cannabis in last month but no selling of any other drug *Non-users*: all with valid responses to cannabis supply question, who report no selling of any other drug in the last month	13,237	3.5
Indicator	Definitions	No. of valid responses	Sample mean
Annual number of shop thefts	Self-reported number of shop thefts in last 4 weeks $\times$ 13	17,721	34.5
Annual number of acquisitive crimes	Self-reported number of episodes during relevant reference period of: shop theft, begging, handling stolen goods, prostitution, controlling prostitution, vehicle theft, thefts from vehicles, domestic and other burglary, personal and shop robbery, theft from the person, financial and benefit fraud; converted to annual basis.	17,158	57.4
Annual income from acquisitive crime	Self-reported summed annual net income from acquisitive crimes, with follow-up check on the total	18,770	£2,222
Annual number of violent crimes	Self-reported number of episodes during relevant reference period of: personal and shop robbery and assault, converted to annual basis.	19,183	2.0

Table A2 Measures of drug use and crime: Offending, Crime and Justice Survey 2003-6

Indicator	Definitions	Sample nos. of users and non-users	Sample prevalence (%)
Heroin user	*Users*: self-reporting heroin use in last month *Non-users*: all with valid responses to heroin questions	15,483	0.17
Cannabis-only user	*Users*: self-reporting use of cannabis but no use of heroin, cocaine or crack in the last month *Non-users*: all with valid responses to drug questions, who report no use of heroin, cocaine or crack in the last month	14,942	9.29
Cannabis-only supplier	*Users*: self-reporting selling of non-class A drugs in last month but no selling of class A drugs *Non-users*: all with valid responses to non-class A supply question, who report no selling of class A drugs in the last month	15,460	0.90
Indicator	Definitions	No. of valid responses	Sample mean
Annual number of shop thefts	Self-reported number of shop thefts in last year	15,526	0.064
Annual number of acquisitive crimes	Self-reported occurrence of benefit fraud in last year and numbers of episodes of: shop theft, vehicle theft, thefts from vehicles, domestic and other burglary, personal and shop robbery, theft from the person.	15,219	0.112
Annual number of violent crimes	Self-reported number of episodes during last year of: personal and shop robbery and assault.	15,306	0.377

Table A3 Characteristics used for matching: AS and OCJS 2003-6

	Sample mean or prevalence (%) [standard error]	
Definition	AS[1]	OCJS[2]
Age at time of interview	30.7 [1.7]	30.8 [0.1]
Female respondent	16.4 [0.5]	49.9 [0.5]
Has been in foster care	16.2 [0.5]	1.2 [0.1]
Age at first arrest	20.9 [0.2]	-
Ever used cannabis	68.8 [0.6]	38.3 [0.5]
Age at first use of cannabis (if ever used cannabis)	15.8 [0.1]	17.6 [0.1]
Left school before age 16	34.3 [0.8]	12.4 [0.3]
Was excluded from school	38.0 [0.7]	3.2 [0.2]
Had difficulty with computer when using CASI	17.6 [0.5]	8.5 [0.3]

Note: [1] Means calculated using weights adjusting for sample design, non-response and arrest frequency. Standard errors calculated allowing for stratified and clustered sample design. [2] Means calculated using weights adjusting for sample design and non-response.