THE GROWTH OF ILLICIT DRUGS MARKETS IN THE UK 1978-99

Stephen Pudney *
Public Sector Economics Research Centre,
Department of Economics
University of Leicester

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ABSTRACT We use a number of aggregate indicators to construct an index of market size for each of eight illicit drugs. These indices can be constructed routinely on an annual basis and are suitable as a baseline against which to judge the impact of anti-drugs policies.

KEYWORDS Illicit drug markets; latent variables; cubic spline trend

JEL CLASSIFICATION C43, C82, K42

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1 Introduction

A major objective of public policy in most developed countries is to reduce the scale of drug abuse. The UK government has committed itself to the brave but extremely challenging target of reducing the use of certain categories of illicit drugs of 25% by 2005 and 50% by 2008 (UKADC, 2000). For targets of this kind, verification presents almost as many problems as attainment, since there currently exists no accepted measure of the size of the illicit drugs market covering an extended period. There seems little point in targeting something that cannot be measured.

A recent Eurostat-inspired attempt at measurement for illicit drugs generally was made by the Office for National Statistics (Groom et.al., 1998) as part of a trial expansion of the scope of national accounts data. Bramley-Harker et. al. (2000) produced alternative estimates for the Home Office, intended as a benchmark for the government's announced target. The aim of these studies was to estimate the size of the illicit drugs market in cash terms for a given reference year (1996 and 1998 respectively) rather than to estimate the trend in market size over time. We would argue that, for the purposes of monitoring policy effectiveness, it is the latter that is important. Given the form of current policy targets, an absolute baseline estimate is unnecessary and simple indices of market size for each category of drug are sufficient. It is the purpose of this paper to construct suitable quantity indices, using only available published indicators of drug use. A study by Corkery (2000), using a range of data sources to examine the growth in cocaine use, is closest in spirit to the approach taken here, although Corkery does not construct a formal index.

2 Methods

Assume there are m indicator variables $Y_{1t} \ldots Y_{mt}$ and that these are observed over a sequence of time periods indexed by $t = 1 \ldots T$. The method rests on the assumption that there is a single common trend and that the indicators are proportional to this trend apart from a purely random multiplicative factor V_{it}. Thus:

$$Y_{it} = A_i \Psi(t) V_{it} \qquad (1)$$

where $\Psi(t)$ is a function of time representing the trend in market size and A_i is a factor of proportionality subject to some scale normalisation. We work with the indicators in logarithmic form:

$$y_{it} = \alpha_i + \psi(t) + v_{it} \tag{2}$$

where lower case symbols indicate the logs of the original variables. This is essentially the same structure as that underlying principle components and factor analysis, except that: (i) there is assumed to be only a single common factor; (ii) after transforming to log form, all factor loadings are equal to one; (iii) the common factor is trended and thus cannot be assumed to be drawn from a latent normal distribution as in factor analysis and (iv) the residuals from each indicator variable are unlikely to be contemporaneously uncorrelated.[1]

We use two alternative methods of estimating $\psi(t)$: one based on year-specific weighted averaging, the other using a more ambitious maximum likelihood approach. After $\psi(t)$ has been estimated, an index of market size (based on 1995 = 100) can be constructed as follows:

$$I(t) = 100 \times \exp\left(\hat{\psi}(t) - \hat{\psi}(1995)\right) \tag{3}$$

2.1 Weighted averaging

Assume that the log indicator variables are contemporaneously uncorrelated so that $\text{cov}(v_{it}, v_{jt}) = 0$ for any pair $i \neq j$. We use the following 3-step approach:

(i) Calculate a initial estimate as the simple average of $y_{1t} \dots y_{mt}$ for each period $t = 1 \dots T$.

(ii) Calculate the m residual variances $\hat{\sigma}_i^2$ from the residuals $\hat{u}_{it} = y_{it} - \hat{\psi}_0(t)$.

(iii) Calculate the refined weighted average of $y_{1t} \dots y_{mt}$, using $1/\hat{\sigma}_1^2 \dots 1/\hat{\sigma}_m^2$ as the weights.

More detail is given in appendix section A1.

[1] Note that the model can easily be extended to include other extraneous variables that may act to perturb the indicator variables. We do not explore this possibility here, but qualitative changes in policing, customs and criminal justice policy might be accommodated in this way using suitable dummy variables, provided there are sufficient pre- and post-innovation observations to allow reliable estimation.

This approach is flexible in that it imposes no a priori form on the trend $\psi(t)$. It is also efficient to the extent that it takes optimal account of the differing degrees of variability of the indicator variables. However, this approach does not take account of any contemporaneous correlation between the residuals v_{it}, and attempts to iterate the method to convergence are unlikely to be successful, since the underlying likelihood function can be shown to be unbounded in certain directions (see appendix).

A further practical disadvantage is that it can be very sensitive to outliers and tends to produce a more ragged appearance than we would expect to be true of the underlying trend.

2.2 A cubic spline approach

The alternative approach introduces a smoothness assumption. The observation period is divided up into short sub-intervals. Within each of these time intervals, the trend can be approximated to a high degree of accuracy by a cubic polynomial. Continuity is imposed on this sequence of cubic functions by restricting successive functions to coincide at the common end-point of their intervals (these points are known as knots). Furthermore, smoothness is imposed by restricting them to have equal first- and second-order derivatives at the knot points. The parameters of this cubic spline approximant are estimated by maximum likelihood, together with the constants α_i and the variances and covariances of $(v_{1t} \ldots v_{mt})$. Technical details of this approach are given in appendix section A2.

3 Results

3.1 Choice of indicator variables

We use the following seven indicator variables which are all available on a drug-specific basis for part or all of the period 1978-1998. However, not all are available for every drug type in every year. The first four indicators relate to drug seizures: the number of Customs & Excise seizures; the quantity seized by Customs & Excise; the number of police seizures; and the quantity seized by police. These variables are published in Corkery (2001) and are available for the period 1978-98 for the major categories of cocaine, heroin, methadone, LSD, amphetamines and cannabis. Crack and ecstasy (MDMA) are also covered in the later years when they become a significant element of the drugs scene.

A fifth indicator, the number of drug-related convictions, cautions, etc, is published in the same source for a slightly smaller set of drug types over 1978-98.

The number of newly-registered addicts was published annually in successive issues of Corkery (1997) up to 1996. The formal registration system ended in that year, so more recent comparable data is not available.

A seventh indicator is only available for five years during the period. The British Crime Survey prevalence for 16-29 year old males is defined as the sample frequency of declared use by male BCS respondents aged 16-29 at the time of interview. We use this in either of two forms: use during the preceding 12 months and use 'ever'. The latter definition does not correspond so closely to the concept of current market size, but it generates slightly higher sample frequencies and therefore gives better statistical precision for the less commonly-used drugs. The group of young males was similarly chosen on grounds of statistical precision, since young males have the highest prevalence rates for most drugs. The BCS figures are available only for the years 1991, 1993, 1995, 1997 and 1999 and are too sparse to be used in the same way as the other indicators within the formal trend estimation procedure.[2] However, they are useful as a rough check on the constructed quantity indices and can be incorporated in a different way. Note that there is a possible problem with our use of the first wave of BCS, which used conventional paper-based interviewing rather than the less intrusive computer-based self-completion approach used since. This may have caused an understatement of usage in 1991 relative to the later years. These indicators are displayed for each of the main drug categories in Figures 1-8. For each series the mean relative (the observation divided by the overall sample mean) is plotted against time. In general these plots present a coherent picture. For each drug category the various indicators generally display broadly similar trends over time, which in turn tend to be confirmed by the BCS prevalence figures.

[2] Since the BCS asks about use in the previous 12 months, the figures do not correspond exactly to the calendar year. This is a minor issue that makes little difference to the results.

However, there are some anomalies for heroin, methadone and LSD. The trend rate of increase in heroin use sharply increased in the 1990s according to all indicators except the number of Customs and Excise seizures. Given the rising trend in quantities seized, this suggests a shift towards fewer, but larger import batches or alternatively a shift in the interception strategy used by Customs and Excise. We deal with this by omitting the anomalous indicator from the trend estimation procedure for heroin. The indicators for illicit methadone show no clear trend, and Customs and Excise seizures (especially quantity) are particularly erratic. However, there does seem to be a fair degree of agreement about a sharp rise since 1993-4. For LSD, all indicators except the BCS prevalence figures tell a similar story of a slowly rising trend until the early to mid 1990s, followed by a significant decline. In contrast, the BCS figures suggest a rising trend during the 1990s, possibly as a consequence of sampling error. We consider the issue of BCS sampling error in section 3.3 below.

Despite these few anomalies, our analytical approach seems broadly in line with the evidence in Figures 1-8 and we now compare the results of applying the weighted average and maximum likelihood estimators.

3.2 Market size estimates

The results of applying the weighted average approach are given in Table 1 and Figures 9-16. Estimation covers the years 1978-99 for all drugs except Ecstasy and Crack, which were negligible before 1989. The problems with these results are obvious. The method lacks any device to produce temporal smoothing of the estimated index. As a consequence, the resulting indices are very erratic and show some implausibly large year-to-year movements. These short-term fluctuations could be reduced by introducing a moving average element or other smoothing device to the calculation. However, the cubic spline approach seems a more promising way forward, with the crude weighted average estimates used as a rough check on the results.

Pure cubic spline estimates are given in Table 2. The trend has been specified to have five cubic segments, with the knots chosen to correspond to the years 1983, 1988, 1992 and 1996 for all except the shorter Ecstasy and Crack series, where we use three segments with knots at 1992 and 1996.

TABLE 1 Indices of aggregate drug use: Weighted average approach

Year	Cocaine	Heroin	Cannabis	Amphetamines	LSD	Methadone	Ecstasy	Crack
1978	9.80	6.13	11.49	2.78	28.86	41.27	0	0
1979	10.99	7.92	13.81	3.80	40.72	62.36	0	0
1980	14.89	8.78	14.27	3.66	29.41	79.32	0	0
1981	17.16	12.41	16.29	6.62	46.60	85.51	0	0
1982	14.65	16.66	15.16	8.12	64.52	68.33	0	0
1983	24.21	28.12	20.33	12.68	58.92	46.08	0	0
1984	32.81	42.75	23.66	16.31	89.62	75.97	0	0
1985	27.19	47.98	22.61	20.91	58.30	98.96	0	0
1986	25.47	36.81	27.21	21.69	41.42	100.73	0	0
1987	33.21	31.24	23.71	22.21	25.04	53.25	0	0
1988	37.70	32.31	40.98	23.84	41.18	49.66	0	0
1989	65.30	38.07	72.39	23.03	86.61	110.27	6.05	10.92
1990	64.58	42.99	59.89	35.54	143.60	45.92	10.73	21.94
1991	68.55	42.03	66.35	49.08	139.19	87.93	52.73	31.04
1992	80.18	47.00	74.08	73.34	139.60	111.29	60.96	47.65
1993	82.33	58.99	85.03	87.85	186.28	88.34	51.64	72.86
1994	86.58	71.28	99.76	104.14	153.10	51.07	107.48	94.13
1995	100	100	100	100	100	100	100	100
1996	118.88	125.31	106.95	158.11	86.95	190.85	230.11	100.68
1997	184.64	187.10	130.78	171.08	56.59	374.95	147.31	163.93
1998	228.37	190.48	142.61	129.64	43.58	360.01	171.82	190.93
1999	269.52	193.04	108.65	112.73	40.64	328.49	257.01	171.08

TABLE 2 Indices of aggregate drug use: Cubic spline approach

Year	Cocaine	Heroin	Cannabis	Amphetamines	LSD	Methadone	Ecstasy	Crack
1978	6.56	7.36	18.67	7.96	30.94	34.77	0	0
1979	5.63	6.22	21.47	7.36	25.67	37.13	0	0
1980	6.35	7.62	23.69	8.61	29.30	43.03	0	0
1981	8.56	11.64	25.56	11.56	39.68	51.29	0	0
1982	12.46	19.09	27.49	16.17	55.01	59.55	0	0
1983	17.79	28.97	30.02	21.35	67.39	63.86	0	0
1984	23.07	36.28	33.77	24.75	65.72	61.01	0	0
1985	27.46	38.65	38.98	25.97	54.77	53.83	0	0
1986	30.95	37.41	45.82	26.10	43.72	46.31	0	0
1987	34.11	35.16	54.37	26.55	37.48	40.98	0	0
1988	37.96	34.25	64.62	28.93	38.69	39.40	0	0
1989	43.66	36.36	76.21	35.06	51.55	42.63	0.16	7.91
1990	51.46	41.45	87.98	45.51	79.64	50.12	5.17	16.09
1991	61.11	49.15	97.96	59.88	122.57	60.63	22.82	35.40
1992	71.88	58.80	103.67	75.52	161.48	71.55	37.96	66.76
1993	82.56	69.42	103.69	87.62	163.22	79.56	54.07	91.26
1994	92.21	82.18	101.09	95.18	134.44	87.10	75.56	99.11
1995	100	100	100	100	100	100	100	100
1996	105.16	128.29	104.47	104.95	74.44	128.29	121.06	109.62
1997	108.89	172.77	115.41	110.45	59.95	182.33	133.17	142.72
1998	120.52	216.38	115.57	104.46	51.19	213.74	148.17	184.26
1999	157.46	216.81	86.52	77.35	44.32	143.19	190.95	184.08

3.3 Consistency with BCS prevalence trends

The British Crime Survey (BCS) has incorporated a self-reported drug use element in every alternate year since 1992. Restricting attention to past drug use reported by 16-29 males, these establish five estimated points on the trend in prevalence. For drugs with sufficiently high prevalence (cocaine, amphetamines, cannabis, LSD and ecstasy) we measure past use as the proportion of 16-29 year-old males who report consumption in the last year. For less widely-used drugs (heroin and crack) we use the proportion of the same group reporting any past use ever. Methadone is a rarely-used drug whose use is not measured with adequate precision. We therefore make no use of BCS data for methadone.

We assume that the log BCS prevalence rate for any drug, $\bar{y}_{0t}$, satisfies the same relation (2) as the other indicators. However, there are only five BCS observations for each drug and it is not feasible to include BCS data directly in the maximum likelihood process.

There are too many additional parameters α_0, var(v_0) and cov(v_0, v_1) ... cov(v_0, v_m) to be estimated from so few observations.

This problem can be solved by assuming that the error term v_{0t} is due solely to BCS sampling error and is independent of the residuals of other indicator series. Under these conditions the covariance parameters are all zero and it is possible to use conventional sampling variance formulae to estimate var(v_{0t}) directly. Appendix section A3 gives the details of this extension to the maximum likelihood estimator.

The results are given in Table 3 and they are compared graphically with the weighted average estimates and the BCS prevalence averages in Figures 9-16. The conclusions are striking. Since 1995, the evidence suggests that there has been a dramatic rise in cocaine, heroin and crack consumption (135%, 104% and 84% respectively). There is also clear evidence of a large increase in consumption of ecstasy (53%) and illicit methadone (43%). Cannabis and amphetamine consumption appears to have levelled off or fallen, while LSD use has declined strongly since the early 1990s. Although there are discrepancies of detail between the three estimated trends and between the paths of the alternative indicators, there is a remarkable degree of agreement on the general form of the trends.

TABLE 3 Indices of aggregate drug use: Cubic spline approach incorporating BCS prevalence rates

Year	Cocaine	Heroin	Cannabis	Amphetamines	LSD	Methadone	Ecstasy	Crack
1978	7.21	7.34	17.35	7.83	31.10	34.82	0	0
1979	6.28	6.19	19.99	7.27	25.81	37.08	0	0
1980	7.10	7.58	22.31	8.52	29.42	42.96	0	0
1981	9.46	11.59	24.38	11.45	39.75	51.23	0	0
1982	13.51	19.03	26.33	16.00	55.01	59.56	0	0
1983	18.84	28.87	28.43	21.10	67.34	63.92	0	0
1984	23.82	36.10	30.95	24.46	65.73	61.04	0	0
1985	27.67	38.38	34.06	25.69	54.78	53.80	0	0
1986	30.55	37.11	37.95	25.84	43.57	46.22	0	0
1987	33.18	34.90	42.85	26.32	36.95	40.86	0	0
1988	36.67	34.16	49.10	28.71	37.36	39.28	0	0
1989	42.30	36.59	57.01	34.80	48.26	42.56	0.63	7.91
1990	50.27	42.13	66.28	45.19	72.21	50.12	11.79	16.09
1991	60.19	50.37	76.00	59.50	108.85	60.75	34.46	35.39
1992	71.04	60.38	84.71	75.17	143.74	71.77	43.56	66.73
1993	81.28	70.86	90.96	87.46	150.03	79.79	54.63	91.23
1994	90.73	82.99	95.47	95.23	129.39	87.25	74.37	99.09
1995	100	100	100	100	100	100	100	100
1996	110.14	127.76	106.69	104.39	75.11	128.05	120.80	109.62
1997	124.30	172.40	116.02	108.70	59.00	181.50	124.97	142.70
1998	155.33	213.58	118.77	101.84	50.51	210.69	127.17	184.20
1999	235.26	204.07	103.66	75.42	48.73	137.76	153.24	184.07

4 Conclusions

We have constructed an estimated market growth trend for each of eight categories of illicit drugs. This has been done by isolating a common trend factor from a set of concurrent indicator series. Of our three alternative sets of estimates, those in Table 3 are to be preferred at this stage. One should always be aware that any measure of the size of an illicit market is inherently problematic. Nevertheless, if policy is to be based on explicit quantitative targets, this method seems to provide as good a basis for monitoring as is presently feasible.

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Appendix: details of estimators

A1 Local weighted average

In each period $t = 1 \ldots T$, $\psi(t)$ is estimated as:

$$\hat{\psi}(t) = \frac{\sum_{i=1}^{m} y_{it} / \hat{\sigma}_i^2}{\sum_{i=1}^{m} 1 / \hat{\sigma}_i^2} \qquad \text{(A1)}$$

where $\hat{\sigma}_i^2 = \frac{1}{m-1}\sum_{i=1}^{m}\left(u_{it} - \bar{u}_i\right)^2$ and $u_{it} = y_{it} - \hat{\psi}_0(t)$. The function $\hat{\psi}_0(t)$ is an initial inefficient estimate $\hat{\psi}_0(t) = m^{-1}\sum_{i=1}^{m} y_{it}$. A smoothed version of this estimator can be constructed by extending (A1) as a two-sided moving average with respect to t.

A2 Maximum likelihood

The ML method uses a cubic spline form to approximate the unknown function $\psi(t)$. Let T_k and T_{k+1} be the two consecutive knots forming the limits of the kth time interval. For any $t \in [T_k, T_{k+1}]$, $\psi(t)$ is approximated by a cubic function:

$$f_k(t;\lambda_k) = \lambda_{0k} + \lambda_{k1}t + \lambda_{2k}t^2 + \lambda_{3k}t^3 \qquad \text{(A2)}$$

where $\boldsymbol{\lambda}_k = (\lambda_{0k} \ldots \lambda_{3k})$. The full approximation to $\psi(t)$ is then:

$$\psi(t;\lambda) = \sum_{k=1}^{K} \xi_{kt}\, f_k(t;\lambda_k) \qquad \text{(A3)}$$

where $\boldsymbol{\lambda} = (\boldsymbol{\lambda}_1 \ldots \boldsymbol{\lambda}_K)$ and $\xi_{kt} = 1$ if $t \in [T_k, T_{k+1}]$ and 0 otherwise. The vector of spline parameters $\boldsymbol{\lambda}$ is restricted by the set of $3(K-1)$ linear restrictions required to ensure that each pair of successive functions in the sequence $\{f_k(.)\}$ have equal levels and first and second derivatives at the knot that they have in common.

Now rewrite the system of m equations (2) in vector form:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \boldsymbol{\iota}\psi(t;\boldsymbol{\lambda}) + \boldsymbol{\varepsilon}_t \qquad \text{(A4)}$$

where $\boldsymbol{\iota}$ is the $m \times 1$ vector of ones. We assume that the error vector $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega})$. Now suppose that there may be missing data on some of the indicator variables. To handle this, define for each period t a selector matrix S_t constructed as follows. In period t let there be p_t

non-missing observations among the m indicator variables. Then take an $m \times m$ identity matrix I and form S_t by assembling the rows of I which correspond to the p_t non-missing elements in y_t. Assuming normality for $\boldsymbol{\varepsilon}_t$, the log-likelihood function can then be written:

$$\ln L(\alpha, \beta, \lambda, \Omega) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln|S_t \Omega S_t^{'}| - \frac{1}{2}\sum_{t=1}^{T} e_t^{'} S_t^{'}\left[S_t \Omega S_t^{'}\right]^{-1} S_t e_t \qquad \text{(A4)}$$

Note that there is a potential identification issue here. The order of the polynomial $\psi(t)$ is critical. If it is so high that an essentially perfect fit is possible for any of the underlying series, then the log-likelihood can be made arbitrarily large by choosing the coefficients of $\psi(t)$ to achieve this and then allowing the corresponding variance parameter in $\boldsymbol{\Omega}$ to got to zero with all other parameters fixed at arbitrary values. Thus, the smoothing introduced by the use of a polynomial trend is desirable in its own right but also necessary for the method to work.

A2 Incorporating BCS prevalence estimates

Let S = {1991, 1993, ...} be the sequence of dates of the five BCS figures. For each we can construct an estimate of the sampling variance, s_{0t}. Then, asymptotic arguments establish that $\bar{y}_{0t} \sim N(\alpha_0 + \psi(t), s_{0t}^2)$. This introduces a new set of likelihood terms which extend (A4) in the following way:

$$\ln L^* = \ln L(\alpha, \beta, \lambda, \Omega) + \sum_{t \in S} \ln\left[\frac{1}{s_{0t}}\phi\left(\frac{\bar{y}_{0t} - \alpha_0 - \psi(t)}{s_{0t}}\right)\right] \qquad \text{(A5)}$$

where $\phi(.)$ is the pdf of the standard normal distribution.

However, the survey standard errors s_{0t} are not directly available. A set of design effects (deft) for the prevalence averages are in use by the Home Office (ranging from 1.23 for heroin to 1.5 for cannabis) and we use the average of these for the 1998 and 2000 BCS samples applied to the simple random sampling formula for survey proportions. Allowing for the fact that $\bar{y}_{0t}$ is in log form, our approximate BCS variance formula is:

$$\text{var}(\bar{y}_{0t}) = \frac{deft^2 \bar{y}_{0t}[1 - \bar{y}_{0t}]}{\bar{y}_{0t}^{\,2} n_t} \qquad \text{(A6)}$$

where n_t is the number of 16-29 year-old males in the BCS sample.

Figure 1 Cocaine market size indicators

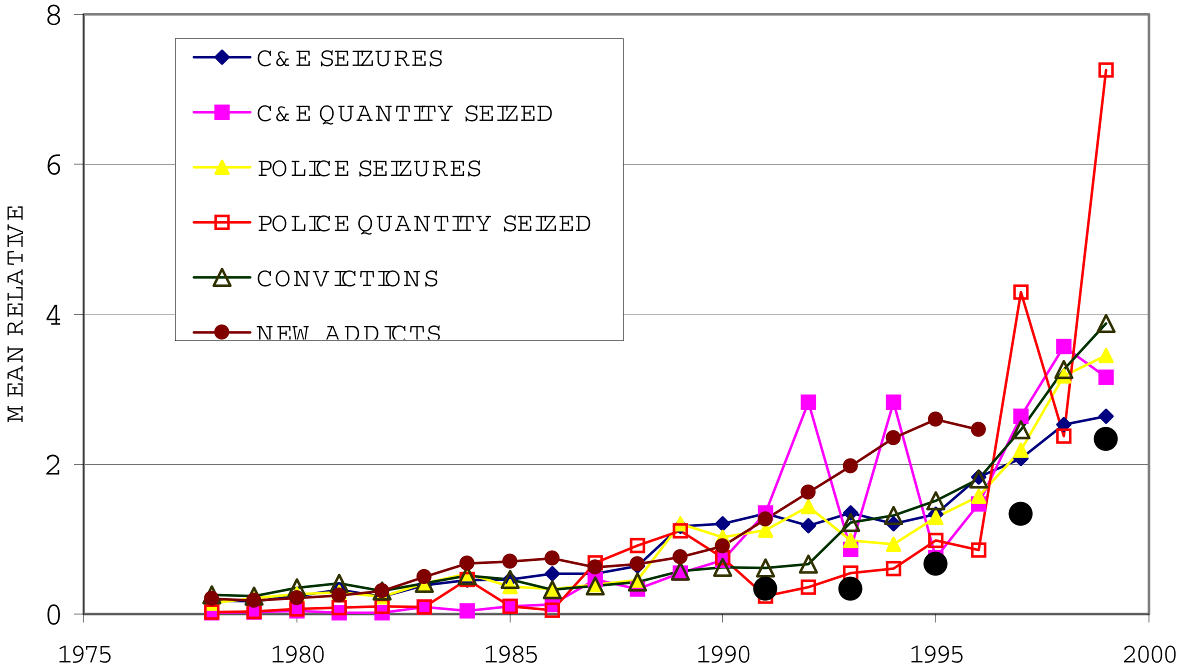

FIGURE 2 Heroin market size indicators

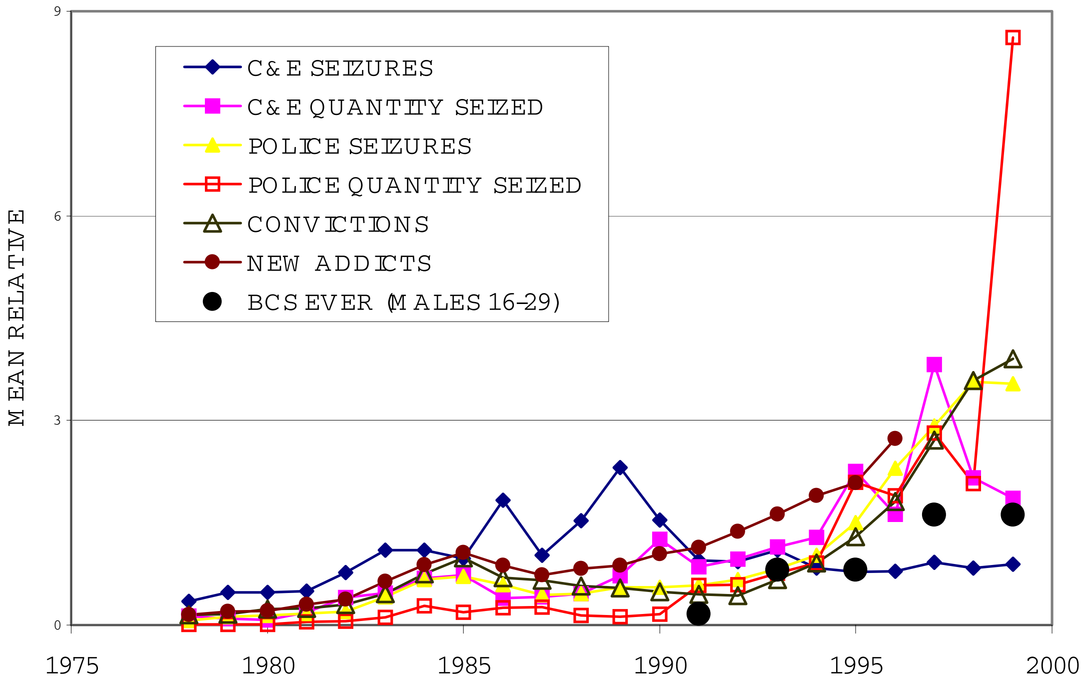

Figure 3 Cannabis market size indicators

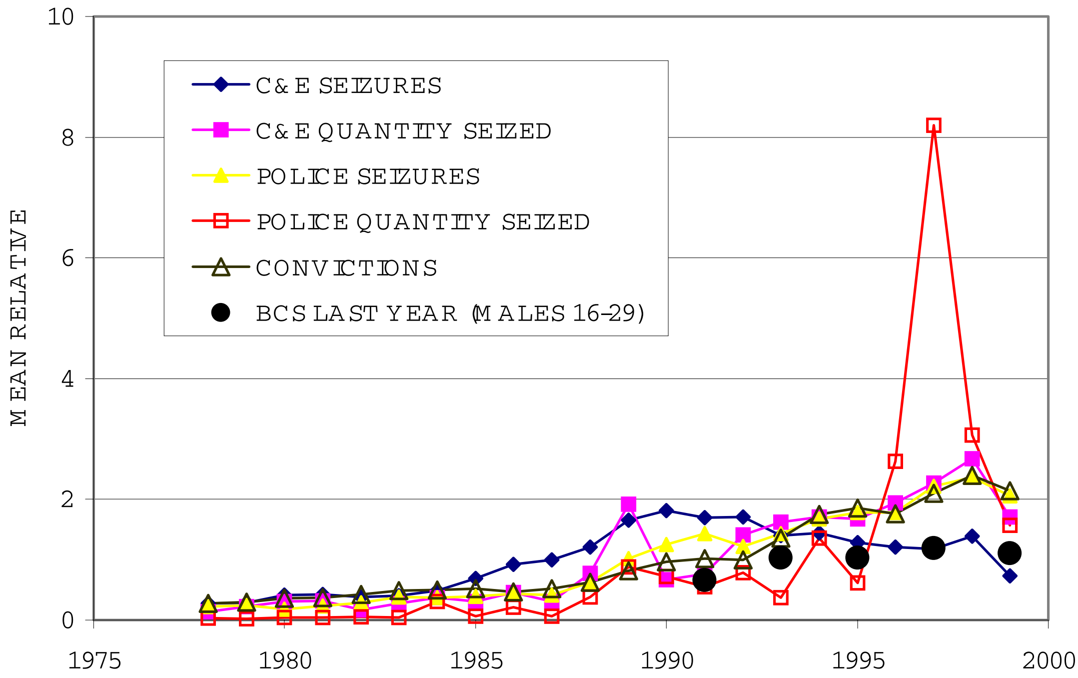

Figure 4 Amphetamine market size indicators

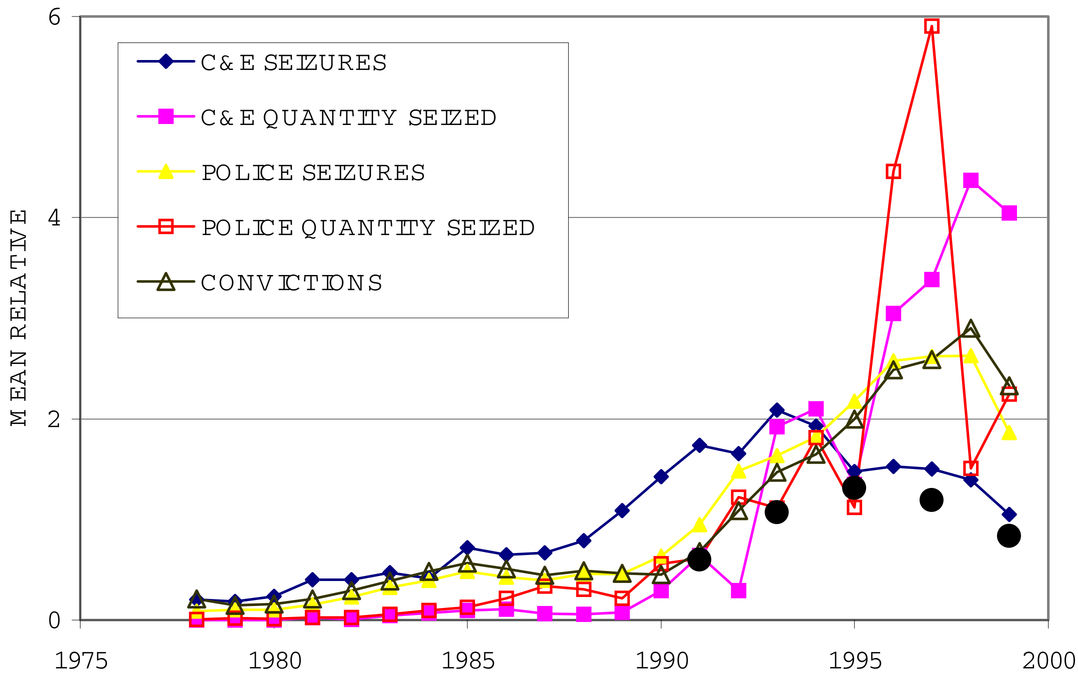

Figure 5 LSD market size indicators

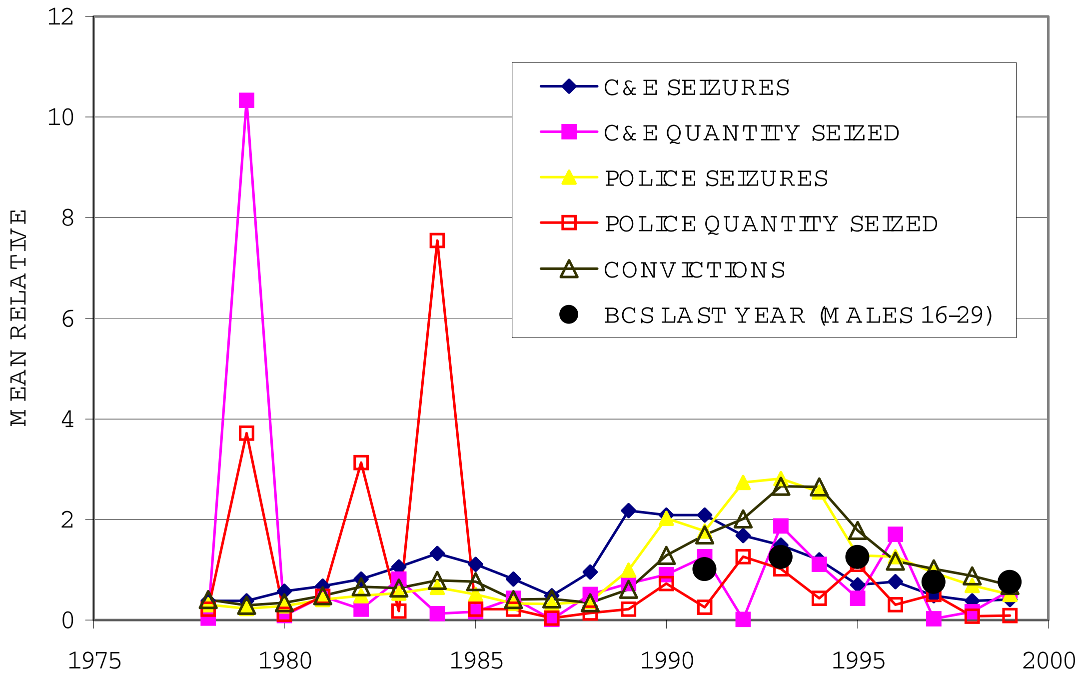

Figure 6 Methadone market size indicators

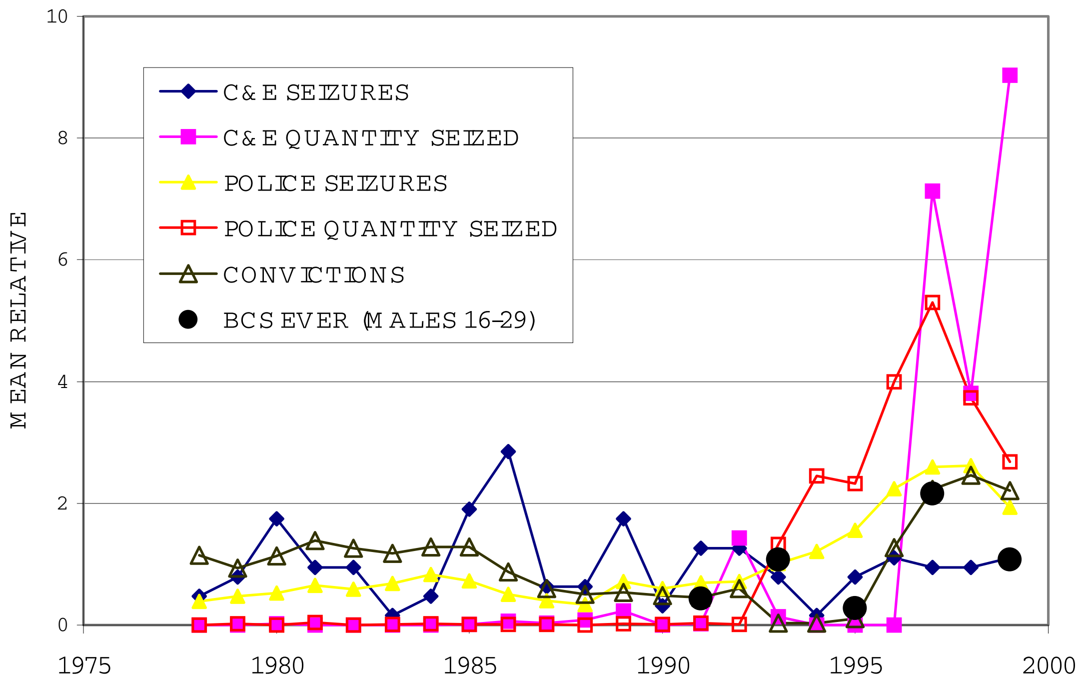

Figure 7 Ecstasy market size indicators

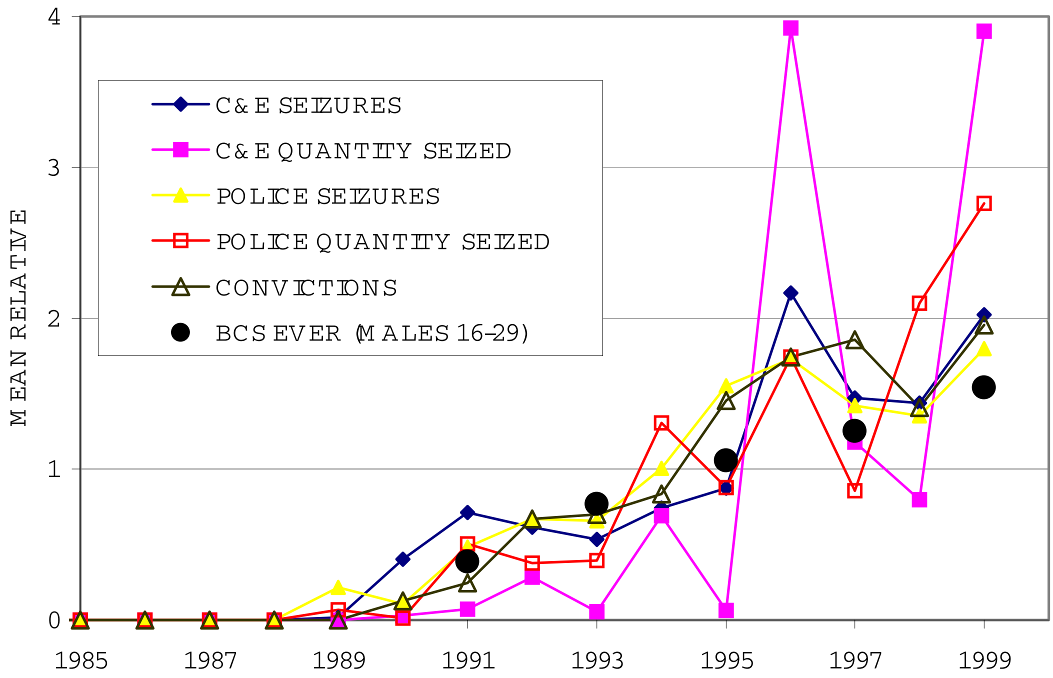

Figure 8 Crack market size indicators

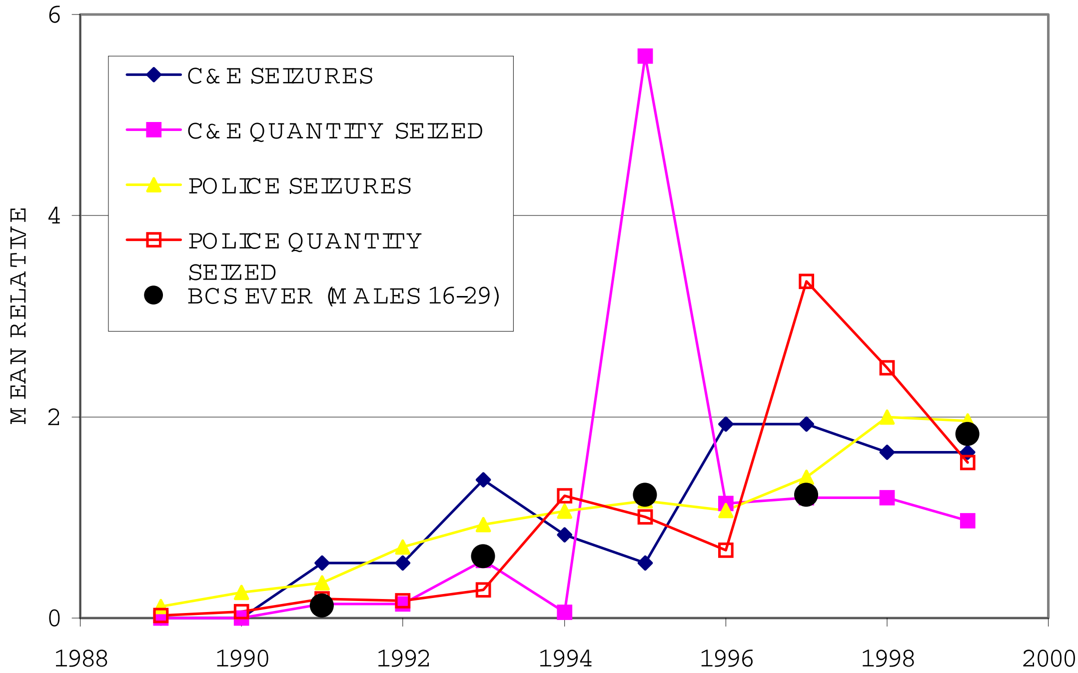

Figure 9 Indices of market size for cocaine

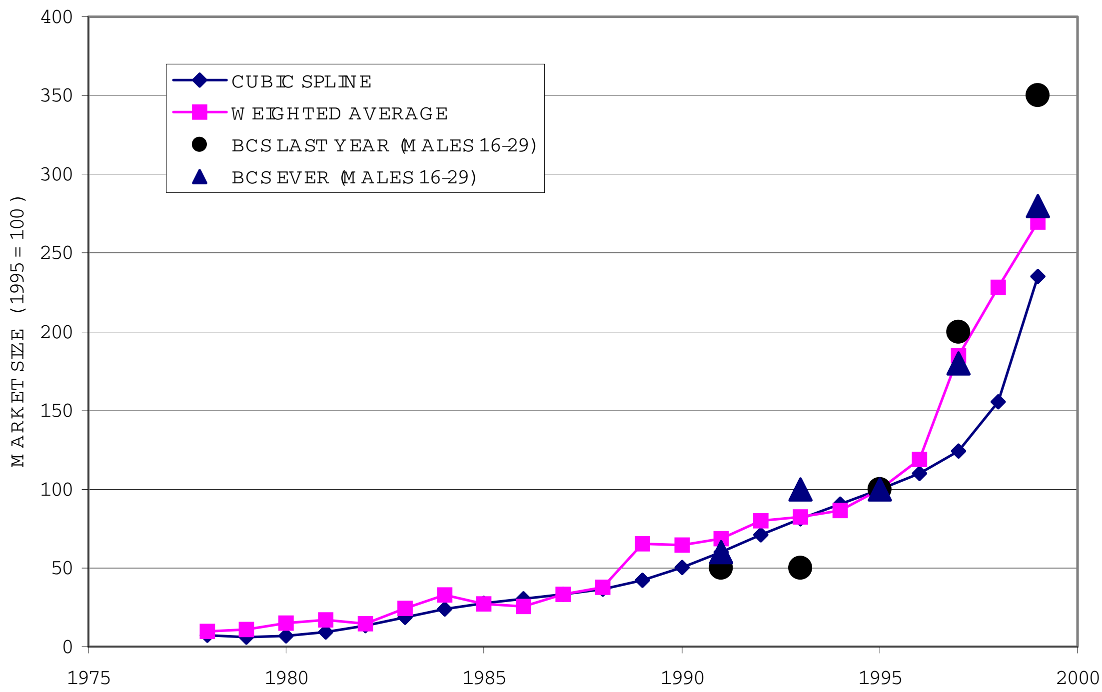

Figure 10 Indices of market size for heroin

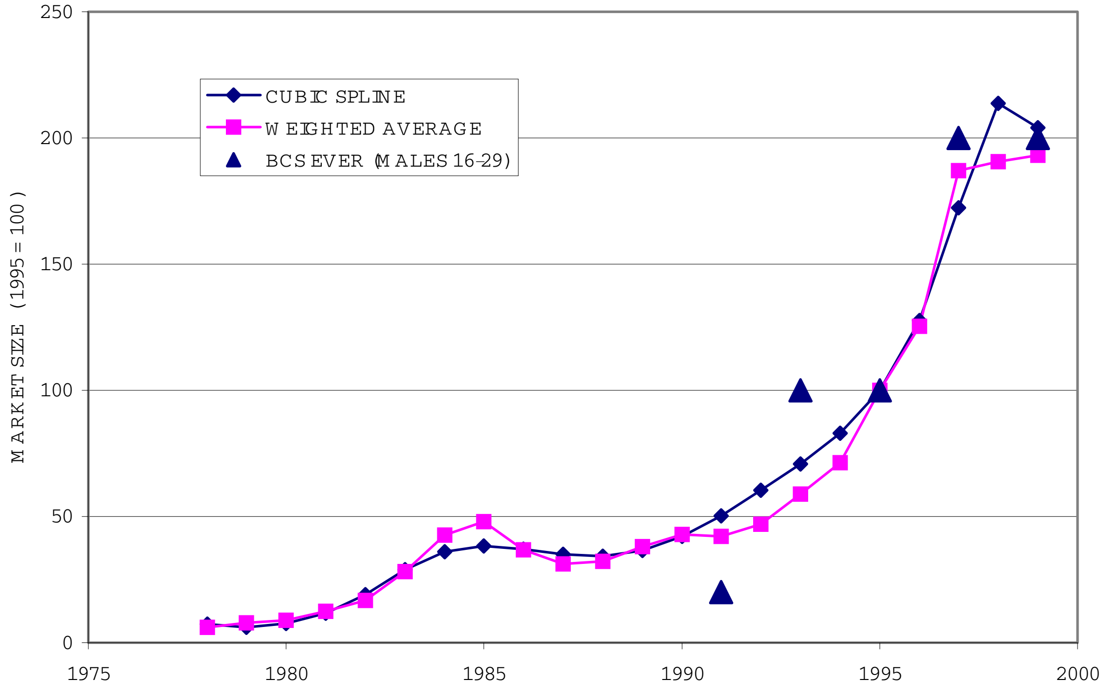

Figure 11 Indices of market size for cannabis

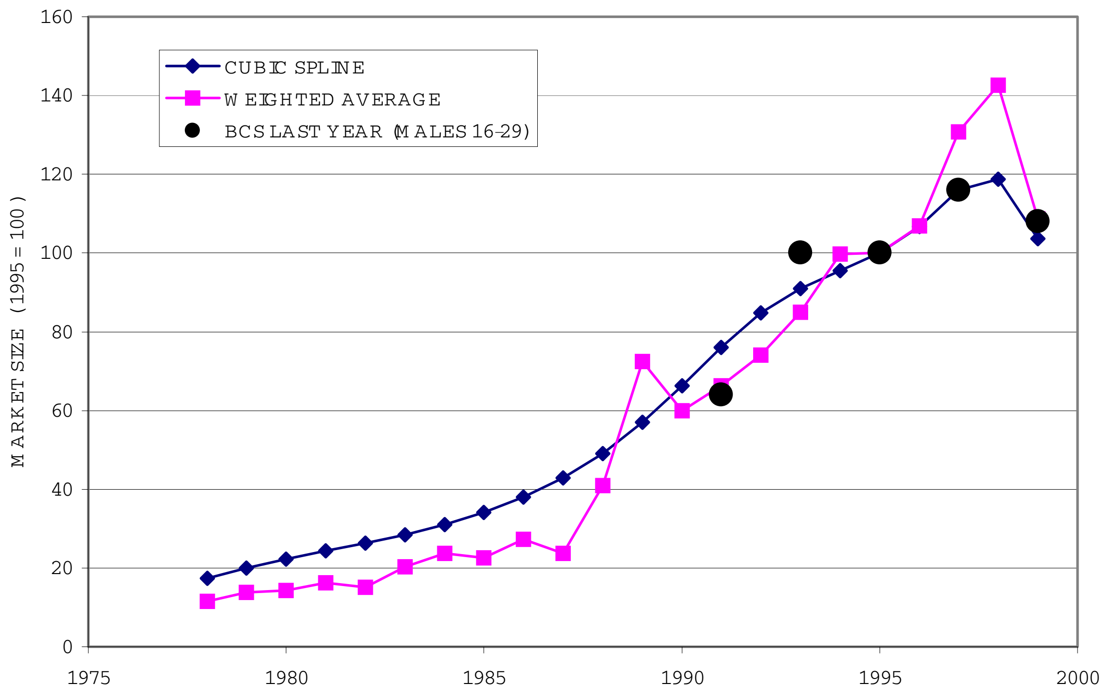

Figure 12 Indices of market size for amphetamines

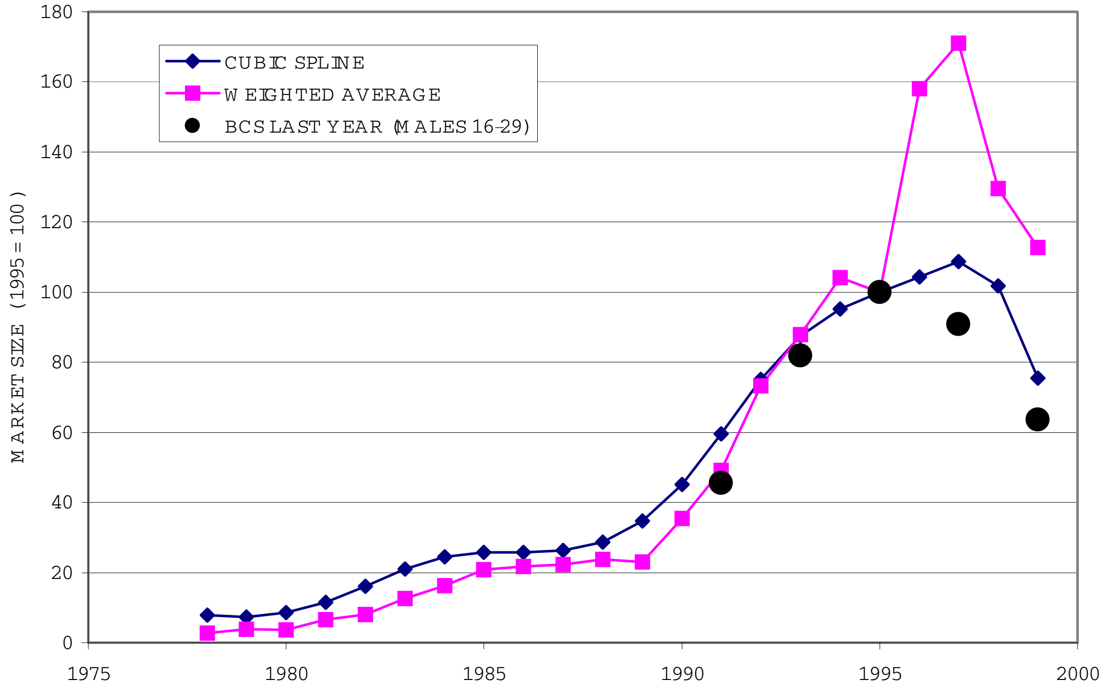

Figure 13 Indices of market size for LSD

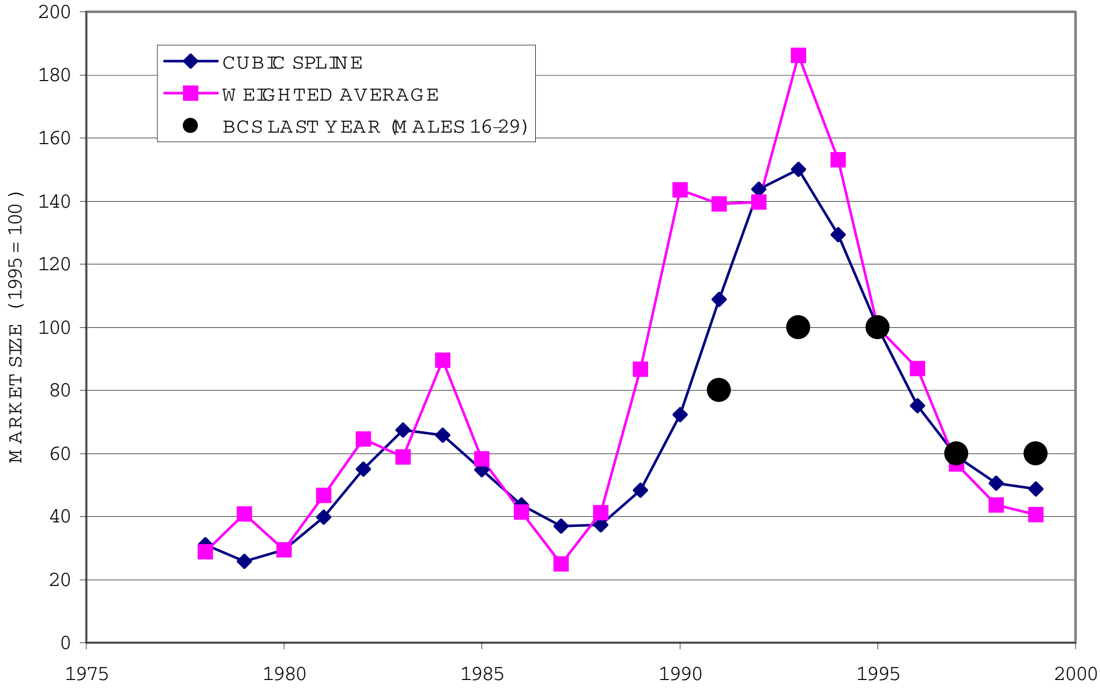

Figure 14 Indices of market size for methadone

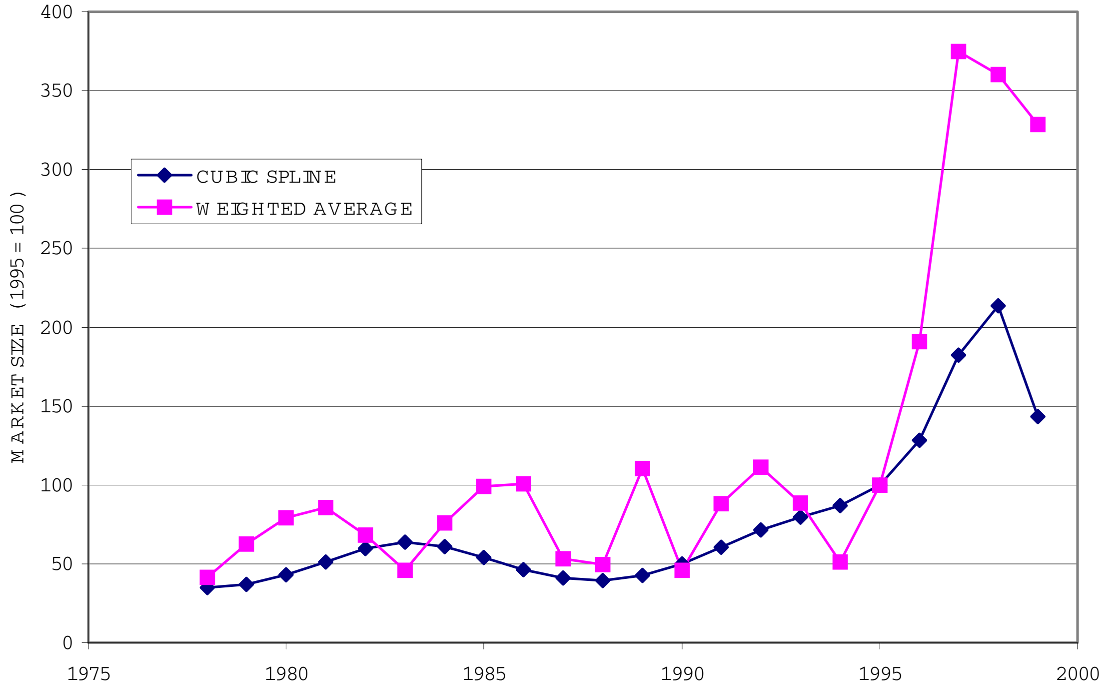

Figure 15 Indices of market size for ecstasy

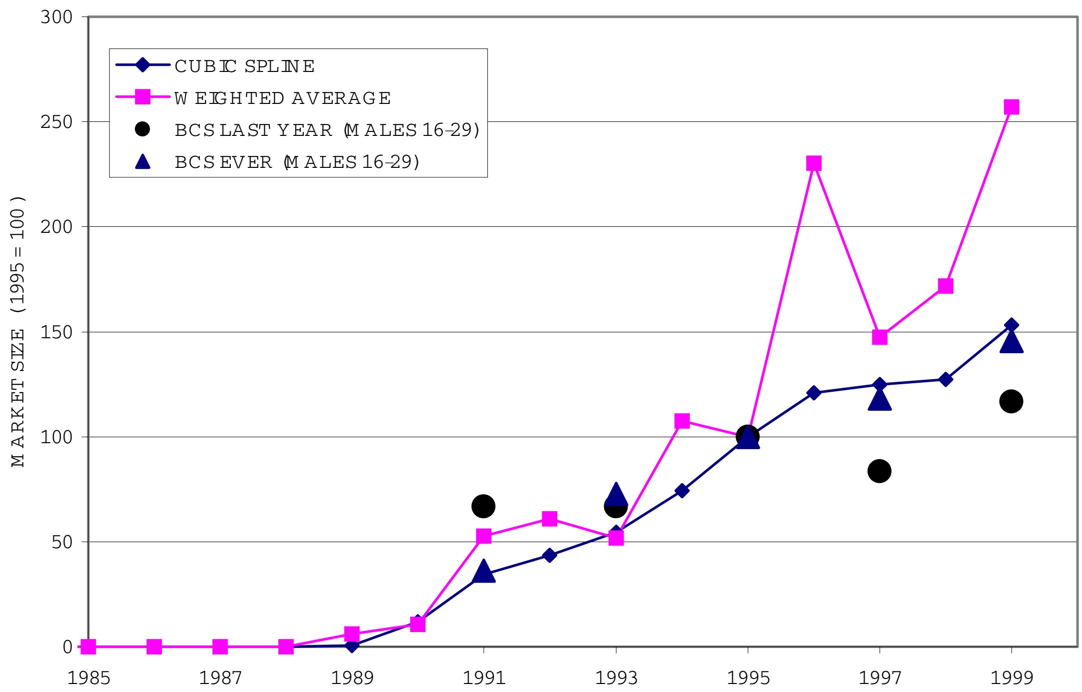

Figure 16 Indices of market size for crack