DIFFERENTIATION OF PERIOD, AGE, AND COHORT EFFECTS ON DRUG USE

1976-1986

Monitoring the Future Occasional Paper 22

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ABSTRACT

Paper 14 in this series reported analyses that differentiated among period, age, and cohort effects on substance use among American youth 18 to 24 years old, from the high school classes of 1976 to 1982 during the period of 1976 to 1982. The present analyses extend the classes and years to 1986, and the age range to 18-28. This manuscript therefore supersedes Paper 14. The Introduction and Methods sections are only slightly revised, but the Results and Discussion sections are extensively updated.

A cohort-sequential design is employed, based on annual surveys of nationally representative samples of high school seniors, plus follow-up surveys of a subset of each senior class.

Several relevant methodological topics are discussed, including (a) the general analysis approach to distinguishing the inherently confounded effects of period, age, and cohort; (b) strategic analytic decisions that must be made; and (c) the particular modelling technique employed. A total of 18 variables are analyzed, dealing with twelve different drug classes, both licit and illicit. Weighted least squares regression is used to find plausible and parsimonious models to account for the observed variation as a function of age, period, or cohort.

Several different types of period, age, and cohort effects over the last decade are identified. Alcohol use (monthly and occasions of heavy use), and the use of marijuana, cocaine, amphetamines, methaqualone, barbiturates, LSD, psychedelics other than LSD, and tranquilizers all showed period effects. Cigarette smoking, alcohol use (monthly, daily, and occasions of heavy drinking), annual and monthly marijuana use, and annual prevalence of cocaine, amphetamines, barbiturates, LSD, and narcotics other than heroin all showed age effects. Class effects were seen for cigarette smoking and daily marijuana use.

The point is made that these interpretations are not unambiguous, and that there are no definitive ways to differentiate period, age, and cohort effects. It is also pointed out that the differentiation of period, age, and cohort effects is only an early step in understanding substance use, because these effects are really proxies for other more fundamental factors. Nevertheless, differentiating the effects is an extremely valuable step in the search for explanations, because the types of factors accounting for observed changes are likely to be quite different depending on which type of effect is occurring.

INTRODUCTION

Monitoring the Future is an ongoing research project that has surveyed a representative national sample of high school seniors each year since 1975. In addition, the project has surveyed a subset of the participants from each senior class during the years after high school. One of the project's objectives is to distinguish among three distinct kinds of change that may occur in the prevalence of illicit and licit drug use:

(1) changes with time, reflected across all age groups (referred to as secular trends, or period effects),

(2) developmental or maturational changes that show up consistently for all graduating classes (age effects),

(3) sustained or lasting differences among different graduating classes (class or cohort effects).

The cohort-sequential design of the Monitoring the Future study was selected to permit investigation of these different effects. A cohort-sequential design is one in which multiple cohorts are followed across time (Schaie, 1965). We use the term cohort synonymously with high school class; the "cohort" of interest is an educational cohort, that is, all those individuals who are seniors in high school in a given year. Table A indicates the nature of the cohort-sequential design; the base year (senior year) and follow-up (post-high school) data collections are shown for the eleven classes of 1976 through 1986, and for the eleven years 1976 through 1986, along with the modal age at each data collection for each class. (We assume a modal age of 18 for all individuals late in their senior year.)

It should be pointed out that period-age-cohort studies generally cover long periods (decades) and long age-spans (three score and ten). The Monitoring the Future data encompass much shorter time and age spans. Nevertheless, drug usage is an area in which considerable change has been taking place; there was a meteoric rise (from a base not far from zero) in use of illicit drugs in the period from about the mid-1960s to the early 1970s. Since then, change has been more gradual, though still considerable; indeed, certain drugs—for example, cocaine and PCP—have shown dramatic changes since the early seventies (Johnston, O'Malley, & Bachman, 1987a). The rapid change associated with period is quite a different situation than that faced by traditional developmental analysts; for example, two decades ago Baltes (1968) argued that time of measurement is unlikely to be an important influence on the dependent variables of interest to developmental psychologists.

The age-span in the Monitoring the Future data is limited (18 to 28 as of 1986), but these are critical years for age-related changes in substance use. The population under study makes the major social transitions associated with going from high-school to young adulthood.

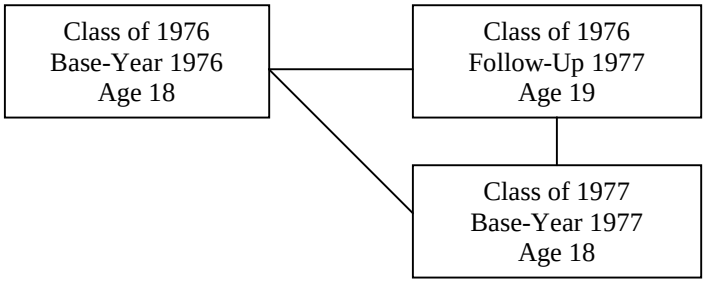
Class effects seem likely to be relatively less important than period or age in this dataset. That is, *a priori*, one would expect certain year effects (because cocaine use is rising in the general population, for example), and certain age effects (because many of the respondents are attaining legal access to alcohol). But it is more difficult to posit class effects, particularly differences between adjacent or nearly adjacent graduating classes.

There is some modest empirical support for expecting relatively little cohort effects. Using data collected in 1975-1976 and in 1983-1984 from cohorts born in 1952 through 1957, Brunswick and Boyle (1979) and Brunswick, Merzel, and Messeri (1985) looked at age, period, and cohort effects on drug use. They found very little in the way of cohort effects, but substantial period and age effects, which varied by specific substance. However, these findings were based on a very specific sample of black people from a single inner city health district of New York City, as well as on a limited age range, and therefore cannot be assumed to be generalizable to broader populations.

Preliminary to presenting the cohort-sequential analyses in which we try to determine which models offer the best fits of the usage data for various substances over the period 1976-1986, we will discuss several relevant methodological topics: (a) the general approach to cohort-sequential analysis, (b) strategic analytic decisions that must be made, (c) procedures for making the best estimates of population values, and (d) the particular modeling technique to be used here.

Cohort Analysis Overview

It is important to note that while the three effects of year, age, and cohort are conceptually distinct and independent, they are not operationally independent. It has long been recognized that the three are inherently confounded (Schaie, 1965). Because any one of the variables is a linear combination of the other two, any model that incorporates all three is unidentified. It is therefore not possible to test any particular model to determine the linear effects of all three. The same is true for any set of completely confounded variables: for example, analyses that employ before, after, and change scores. There are, however, ways to look at the data to determine the most likely sources of variance. Palmore (1978) has suggested one straightforward approach, which it may be useful to review briefly. Consider the following schematic display of data:



Assume that the lines connecting the boxes represent observed differences between the groups indicated on a given variable. The difference represented by the horizontal line includes two kinds of effects: an age effect and a year effect (class is held constant). The vertical line represents both an age effect and a class effect (year is constant). The diagonal line represents both a year effect and a class effect (age is constant).

Now, in the absence of sampling or measurement errors, and if we assume that all the variance is due to age or year or class, there are three possible patterns of findings in looking at the three difference scores represented by the horizontal, vertical, and diagonal lines: (1) no differences, a trivial and uninteresting case; (2) two differences; and (3) three differences. (It is logically impossible to have only one difference; given any one of the three possible differences, there

would be at least one effect, and that effect would have to be reflected in at least one other difference.)

If there are only two non-zero differences, then the most plausible inference is that the type of effect that is common to both differences, and missing from the other difference, is not zero.[1] If there are three differences, there is no definitive way to apportion the effects. Only if one is willing to assert that one of the three is equal to zero can the effects be determined: thus, in the absence of external evidence, and when all three differences are non-zero (as would often be the case), the effects of age, year, and class *cannot* be unambiguously separated.

In the Monitoring the Future data there are 66 such data cells as of 1986, rather than three. The above analytic method could be applied to all 55 triads of cells using one-year intervals, or to all 45 triads using 2-year intervals, etc. This would be obviously be an exhaustive analysis approach, and very unparsimonious in that it imposes no constraints of ordinality, linearity or additivity. It seems preferable to impose some such constraints at least in the initial stages of data analysis in this difficult and complex area. Mason, Mason, Winsborough, and Poole (1973) made a significant contribution to the area by showing that any constraint that removed the complete linear interdependence made the general model identified. An example of one such constraint would be constraining the effects of any two years to be equal. Unfortunately, this technique is not without its problems. One major criticism is that the assumption of additivity is likely to be in error in many cases (Glenn, 1976). Another problem is that the method provides readily interpretable results only when all effects are nonlinear, because pure linear effects are inherently ambiguous; any linear effect can be estimated equally well by that effect or by the other two effects (Glenn, 1981). A more important criticism is by Rodgers (1982), who showed that even seemingly reasonable identifying constraints could have major effects on parameter estimates. Rodgers demonstrated that "Although a constraint of the type described by Mason et al. seems trivial, in fact it is exquisitely precise and has effects that are multiplied so that even a slight inconsistency between the constraint and reality, or small measurement errors, can have very large effects on estimates" (p. 785). Mason and Smith (1981) further pointed out that the usefulness of the age-period-cohort framework depends heavily on strong prior hypotheses about the patterns in the coefficients as well as on specific historical knowledge. In sum, it should be kept in mind that all recent commentators in this area agree that age-period-cohort effects are inherently confounded and that there is no purely statistical way to estimate main (or interaction) effects unambiguously (see also Adam, 1978; Buss, 1973, 1975; Converse, 1977; Costa & McCrae, 1982; Fienberg & Mason, 1979; Pullum, 1977; Rodgers, Herzog, & Woodworth, 1980; Schaie, 1984; Smith, Mason, & Fienberg, 1982).

Analysis Strategy Decisions

Our purpose in this paper is to account for the variation in prevalence rates of various substances in terms of age, year, and class effects. We accomplish this by positing a model and then testing whether that model does indeed account for the observed variation. Because one important desideratum is parsimony, a reasonable starting model would be one that is linear and additive, although as indicated above, all three effects could not be estimated without some additional constraints, constraints that may themselves introduce error. However, if one is willing to make

[1]There are other logical possibilities but they involve very unlikely equal and opposite effects.

some strong assumptions—for example, that cohort effects are zero—then an estimable model may be posited. Given such a model, it can be estimated by using ordinary least squares (OLS) regression. But OLS has certain liabilities. The most salient is that OLS assumes homogeneity of variance, an assumption that is particularly vulnerable when the data to be analyzed are proportions (which is the case here). When the proportions fall in the range of .25 to .75, the choice of methods will almost certainly make very little difference because the results will likely be virtually identical. However, when the proportions are more extreme, and particularly when they are outside the range of .10 to .90, the choice of methods is more important, because the results are likely to be divergent (Knoke, 1975). For several of the drug classes under consideration here, the proportions are under .10. Therefore, weighted least squares (WLS), which can incorporate heterogeneity of variance, is preferable with these data. GENCAT (Landis, Stanish, Freeman, & Koch, 1976) is a specific computer program that can implement WLS.

There are other decisions that need to be made, assuming GENCAT is to be used. The dependent variables of interest here are proportions, but there is the question as to whether the proportions themselves or the log-odds thereof should be analyzed. A problem with proportions is that the model may generate inadmissible predicted values, values outside the logical limits of 0 and 1. One solution often prescribed for this problem is to use the log-odds (or logit) instead of proportions:

$$\text{logit} = \ln(P/1-P)$$

Although P lies between 0 and 1, the logit can take on any value from negative infinity to positive infinity, and no predicted value is inadmissible. Unfortunately, logit analysis results are not as intuitively appealing because the results are expressed in terms of logarithms of odds-ratios instead of in the original metric of proportions. Therefore, in spite of the potential problems with proportions, they will be the dependent variable in these analyses.[2] Reynolds (1977) has summarized this issue:

> Many statisticians, especially those emphasizing the practical aspects of analysis, do not regard the possibility of obtaining inadmissible estimates as a serious problem. As n increases, the likelihood of accepting a model with estimates outside the range of 0 to 1 diminishes, especially if the true proportions are not too close to 0 or 1. If one has a relatively large sample size, they argue, he should not sacrifice the analysis of P's (assuming they are theoretically interesting) for the sake of statistical niceties. (p. 186)

Another decision involves the assumptions to be made. Although the assumption of homogeneity of variance has been dropped, other assumptions have been retained. One of these is that each data collection relies on independent random samples. This assumption is not fully defensible in the current data set for several reasons:

[2]In fact, no inadmissible estimates were produced in any of the results discussed in this report.

(1) Each follow-up data collection is based on a subsample of the base-year sample for that cohort. (One subsample is followed on even-numbered years, and a second, independent subsample is followed on odd-numbered years.)

(2) For any two adjacent cohorts, about half the schools in one sample will be in the other as well. (For non-adjacent cohorts, there is no overlap.)

(3) All base-year samples are clustered by the first-stage sampling unit (PSU).

Each of these sources of covariation—currently assumed to be zero—can later be relaxed (though that requires some difficult estimation of covariances based on individuals, schools, and PSUs); the first set of covariances (among individuals) is likely to be fairly substantial, while the latter two are likely to be small. The effect of leaving the covariances at zero will be to make a given degree of change appear less statistically significant than it actually is.

It is also assumed (for inference purposes) that the data come from a multinomial distribution. A multinomial distribution requires that a "simple random sample of fixed size n is taken and each respondent is placed in a cell according to the levels of the variables cross-classified" (Payne, 1977, p. 125). This situation is not the case; the clustered sample and unequal probabilities of selection (both base-year and follow-up) violate it. We deal with this by adjusting the obtained n's downward to take account of design effects, as is discussed below.

Estimation of Population Values

The next methodological consideration is the quality of the sample data as estimators of population values. The problem to be dealt with is that while we have very good estimates of population values for base-year data, the follow-up data are less accurate, due to the lower number of cases, random selection bias (those selected for follow-up differ somewhat from the total base-year sample due to sampling error), and panel attrition.[3] Since 1978, response rates have been quite good, generally in excess of 75%. Thus, the attrition problem is most severe for the class of l976 followed-up in 1977, but it exists to some extent for all the follow-up data.

The procedure used to estimate prevalence in the follow-up samples is to reweight participating follow-up respondents so that each follow-up panel has (when reweighted) the same base-year prevalence as the total base-year sample for that class-year. For example, suppose 50% of the entire base-year sample reported using marijuana in senior year, but among those participating in a given follow-up panel from that class only 40% had (as seniors) reported such use. The follow-up respondents who had been users in base-year would be weighted 5/4, and follow-up respondents who had been non-users would be weighted 5/6, thus creating a 50% base-year usage rate for the follow-up panel. The follow-up prevalence rates would then be derived by applying these weights to follow-up data.[4]

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[3]Because of unacceptably low participation rates in the 1977 follow-up, the procedures were changed beginning in 1978, with the major changes being the incorporation of a financial incentive and a reduction in the size of the sample; in addition, because of low participation rates in both 1976 and 1977, the class of 1975 was dropped from further analysis.

[4]Alternative procedures have been investigated in other analyses of the follow-up data. One procedure involved an extensive search for important predictors (using base-year variables other

This procedure was carried out for each prevalence measure for each of a number of licit and illicit substances, for each follow-up panel.[5] The adjusted follow-up prevalence measures are, as one would expect, higher than the unadjusted figures. The adjustments are generally small, however, in part because participation rates are fairly high (around 75-80%), and because the financial inducement to participate probably reduces the degree to which willingness to participate varies among subgroups.

Modelling Technique

Assessing goodness of fit. The next set of methodological decisions deals with assessing the quality of fit of a model that describes the data. The GENCAT program reads a set of observed proportions (P), and estimates parameters of a specified model. (The process of selecting a model is described below.) From the estimated parameters, a set of predicted proportions Pis derived. A generalized least-squares goodness-of-fit chi-square statistic is provided, which assesses the overall fit of Pto P. The statistical significance of each individual parameter, as well as any combination of parameters, can also be assessed by a chi-square.

The larger the chi-square, the more the predicted values depart from the observed data values. Thus, for large chi-squares (relative to degrees of freedom), we conclude that the hypothesized model does not fit the data very well, and we say that the probability is low that the differences between observed and predicted values could have arisen by chance. Of course, what we wish to do is to find a model that does adequately describe the data; therefore, we seek to minimize the chi-square and maximize the probability. Note that this is different from the more customary procedure in which the chi-square is used to test for independence; there, one usually prefers to find a large chi-square so that one can reject the null hypothesis of no association. A related departure from customary procedure is that one customarily sets a value to minimize Type I error, usually .05 or .01, so that one is very unlikely to conclude that a relationship exists unless there is strong evidence for it. In searching for a good-fitting model, however, one should be concerned with reducing Type II errors as well, and this concern has the effect of increasing the probability of a Type I error. (A Type II error in this context would be accepting a model with unnecessary parameters included.)

By requiring a very high probability that only chance variation generated the obtained differences between predicted and observed values, we run a danger of excessive Type II errors. High levels ($p > .9$) may actually involve "too good" a fit—that is, the model may include unnecessary parameters (Knoke & Burke, 1980; Bishop, Fienberg, & Holland, 1975). Thus, in what follows, whenever p values are very high, it is likely that there is some degree of "over-fitting." The best protection against this is to demand a certain amount of parsimony, regularity, and reasonableness in the model.

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than use of a specific substance) of participation. Because even the best predictors had little predictive power, the procedure described above provides what we believe to be the best adjustments.

[5]Note that because each follow-up year on a given cohort is based on a different set of respondents, each follow-up year is estimated separately using a separate reweighting.

In addition to the overall chi-square, residuals can be examined. As with ordinary linear regression, these often provide considerable information about where the model is misspecified.

Another useful way to look at the fit of a model is to ask how well the data can be reproduced by using some very simple "baseline" model. This baseline model would include only a constant and no effects due to year, age, or class. Effectively, this predicts each cell value to be equal to that constant. The baseline error chi-square is a measure of how much variability is left in the observed data that cannot be accounted for by the constant. Then models can be fitted that contain more than just a constant, and error chi-squares smaller than the first will be obtained. The resulting decrease in variability can be expressed as a percentage of the total available:

$$\text{Percent} = \frac{\chi^2 \text{ constant} - \chi^2 \text{ fitted model}}{\chi^2 \text{ constant}} \times 100$$

This percentage is analogous to the coefficient of determination (R-squared) for multiple regression (Knoke & Burke, 1980, p. 40). It indicates how much of the variance left unaccounted for by a constant can be accounted for by the parameters estimated in the fitted model. This measure is useful because, unlike the error chi-square and its associated probability, it does not depend on the number of cases.

This observation recalls the earlier question of how to handle n, the number of cases. In the GENCAT program, the number of cases is used as a basis for estimating the variance of each proportion (variance = P*(1-P)/n). For all the models to be examined, n has been set at 500. In fact, n is much larger for base-years, and somewhat larger for follow-ups, but if actual n's were used the model would place very heavy weight on the base-year data (because of its smaller variance) at the expense of follow-up data. Because the base-year data represent all years and all classes, but only one age, larger base year n's can "wash out" age effects in favor of the other variables. We prefer instead to treat each data point equally and allow the algorithm to fit all the data without a bias toward base year.

Selection of a model. As indicated above, we wished at least initially to impose a good deal of parsimony on any model describing the data. We proceeded as follows. First a constant-only model was estimated. If the fit to the data was reasonably close (probability >= .5), we did not try further fitting.[6]

For the measures that showed some variability, the data were displayed graphically and inspected for evidence of "pure" linear age, period, or class effects. Table B presents hypothetical data

[6]The probability values are based on an underlying number of cases set equal to 500. This greatly understates the actual n for base-year data, and, overall, may slightly understate the random-sample equivalent n for follow-up data. Thus, a probability value of .5 is an inflated value, to an unknown extent; based on both intuitive notions and on examination of the data, we believe that any probability much less than .5 leaves room for improvement of the fit.

exemplifying such "pure" effects. In panel 1 of Table B, prevalence rates are equal for all 18-year olds, and also equal for all 19-year olds, but at a higher level; and so on. In panel 2, age makes no difference in the prevalence values, but each successive year's rate is higher than the previous. Finally, panel 3 shows class effects, but no age or year effects. Where the graphical display of the actual data appeared to show specific linear effects, a model that incorporated only that effect was tried and evaluated. The pattern of residuals was also inspected to infer where the model might be inaccurately specified. Finally, nonlinear effects were added where it seemed to be necessary. The shape of the nonlinearity was constrained to be reasonable; for example, increasing linearly, then decreasing linearly. In all cases, only "statistically significant" parameters were retained. (Nominal statistical levels are obviously not to be taken literally with this ad hoc procedure.)

METHODS

The data for this report come from the Monitoring the Future project, an ongoing study of high school seniors conducted by the Institute for Social Research at the University of Michigan. The study design has been described elsewhere (Bachman & Johnston, 1978; Bachman, Johnston, & O'Malley, 1987; Johnston, O'Malley, & Bachman, 1987a); briefly, it involves nationally representative surveys of each high school senior class, beginning in 1975, plus follow-up surveys mailed each year to a subset of each senior class sample.

Samples and Survey Procedures

A three-stage national probability sample leads to questionnaire administrations in about 130 high schools (approximately 110 public and 20 private), and yields about 17,000 respondents each year. The response rate is generally about 80% of all seniors.

In addition to the senior year, or base-year, data collection, annual follow-up surveys are mailed to a subset of each base-year sample for a period that will extend to sixteen years following graduation. From each senior class, 2,400 seniors are selected for follow-up, and randomly divided into two groups, each group numbering about 1,200. Members of one group are invited to participate in the first year after graduation, and every two years after that; those in the other group are invited to participate in the second year after graduation, and every two years after that. The result of this approach is that individual participants are surveyed on a two-year cycle, beginning either one or two years after graduation. Respondents are paid $5 for each follow-up participation. The follow-up samples are drawn so as to be largely self-weighting; however, because the primary focus of the study is on drug use, users of illicit drugs are over-sampled for follow-ups (by a factor of three to one). Weights are used in all analyses to adjust for the differential selection probabilities. These follow-up procedures were initiated beginning with the follow-up of 1978; in addition, the class of 1975 was dropped from further analysis, because of low participation rates in both 1976 and 1977. The class of 1976 follow-up of 1977 differed from all succeeding follow-ups in that respondents were not paid for participation, so response rates in that year were somewhat lower. Otherwise, response rates have generally been over 75%. Table C provides the percent participating for each year for each class.

Drug Use Measures

All items employ close-ended response alternatives suitable for optical scanning. Use of alcohol and illicit drugs are measured by questions having the following standard format:

> On how many occasions (if any) have you used [*name of drug category*]...
>
> a.)...in your lifetime?
>
> b.)...during the last 12 months?
>
> c.)...during the last 30 days?

Seven response categories are available: 0 occasions, 1-2 occasions, 3-5, 6-9, 10-19, 20-39, 40 or more. The illicit drugs asked about are marijuana, cocaine, amphetamines, methaqualone (quaaludes), barbiturates, LSD, psychedelics other than LSD, tranquilizers, heroin, and narcotics other than heroin. (Legitimate medical use of the psychotherapeutic drugs is not treated in this paper. See Johnston, O'Malley, and Bachman (1987b) for findings on this topic.) An additional question about heavy use of alcohol asks respondents how many times in the last two weeks they had five or more drinks in a row.

The questions about cigarette use depart from the above standard format because of the different consumption pattern for cigarettes. One question asks the respondent to characterize current and past use (never; once or twice; occasionally, but not regularly; regularly in the past; regularly now), and a second question asks about use in the past 30 days (not at all, less than 1 cigarette per day, 1-5 cigarettes per day, about one-half pack per day, about one pack per day, about one and a half packs per day, 2 packs or more per day).

RESULTS

A total of 18 variables were analyzed, dealing with 12 different drug classes. For all nine illicit drugs other than marijuana, only an annual use measure was included; for marijuana, annual, monthly, and daily use were included. For alcohol, monthly and daily measures were included, as well as a measure of heavier drinking within the past two weeks. For cigarette use, measures of monthly and daily use of at least one cigarette per day and daily use of at least 1/2 pack per day were included.

Figures 1 through 18 display for each of these variables the longitudinal trajectories of each high school class. The tabular data underlying each figure (plus some additional information about model-fitting) are in Tables 1 through 18, respectively. In interpreting the data and deriving plausible explanations for them in terms of year, age, and class effects, a caveat should be kept in mind:

> ...the cohort analyst should never plunge directly into a rigorous analysis without first applying the simpler methods, and the researcher should never forget that rigorous methods cannot overcome the fact that any set of cohort data is always susceptible to at least two interpretations (in terms of the kind of effects reflected in it). (Glenn, 1977, p. 61)

Inspection of Figures 1 through 18 should be done with an additional caveat in mind: it is easy to "overinterpret" small differences in proportions, compared to proportion-of-variance-explained

kinds of measures. For the data analyzed here, statistically significant effects can be associated with individual-level multiple R-squares of 0.5% or less. Sampling variations, differential response rates, etc., can result in small changes that may appear large in the scale of Figures 1 through 18.

In sum, the following paragraphs rely partly on "rigorous" methods, and partly on intuitive interpretation based on an understanding of the phenomena being investigated. It should be clear that there is considerable room for alternative explanations of the data.

Table D presents a summary overview of the results of fitting a model to each of the drug use variables. For each variable, the table indicates: (1) the nature of the effects that seem to account best for the observed data; (2) the probability that deviations from a constant-only model could have been observed by chance, given that such a model is an accurate representation of reality; (3) the corresponding probability from the fitted model; and (4) the percent reduction in error variability accounted for by the fitted model relative to a constant-only model. A high percentage reduction indicates that the fitted model is leaving little additional variation that can be explained by additional parameters. Numeric entries indicate a linear effect unless otherwise noted.

In several cases, a plausible model to fit the data clearly required a non-linear effect, though in all cases only additive models have been employed. For example, some drugs appeared to show a rise and fall with time or age during this historical period. Rather than leave all effects as simply linear, the following procedure was used. Where linear models seemed inappropriate, the figures were inspected to determine which effects seemed strongest, and what the general shapes of those effects were. Code values were assigned based on the general shape, and then, using only one or two effects (with a single degree of freedom each), additional models were tested to see if close fits could be obtained. These effects, designated in the summary table, are primarily of two types: (1) Bilinear effects of age and year, reflecting first a linear increase, and then a linear decrease. In these cases, the slopes are equal, but opposite in sign. (Unequal slopes are possible, but as it happens, equal values seemed adequate to describe the data.) (2) An age or year effect, linear from one point to another, and constant otherwise. The inflection points vary for the various measures.

Because these fitted functions were selected on the basis of inspection of the data, they often provide an excessively good fit; and this makes any probabilistic statement about the likelihood of the model's "truth" very tentative. Clearly, this procedure is not the classical approach of stating an *a priori* hypothesis, and then testing that hypothesis with data. The procedure is instead more of a "data-fitting" exercise, in which we try a posteriori to find a plausible model to account for the observed variation. Put another way, it is an attempt to achieve a reasonable retrospective interpretation of what happened during a particular historical period across a particular age band. Statistical probabilities are not a basis for deciding to accept or reject hypotheses, but rather are used to guide the interpretation of the data.

An important statistic, given in Table D, is the probability that random error (chance) could account for the variability left after a constant is fitted. (See the column labeled "constant only.") When the value in this column is very high, it means that the data are not showing much variation around the constant, and there is little point in searching for a more complex model to improve on an already good fit. One of the measures in Table D does show a high value for the

baseline model (namely, heroin), and the proper inference is that it simply is not varying much over the study period.[7]

General Comments on Earlier Results

In the analysis of 1976-1982 data, we had found a variety of different effects. Cigarette use generally showed primarily (but not exclusively) class (or cohort) effects, alcohol use showed primarily age effects, and marijuana use showed primarily secular trend (or year) effects. cocaine use showed both age and year effects. The other illicit drugs generally showed less change, with a decreasing secular trend being most common.

These earlier analyses covered the classes of 1976-1982, the years 1976-1982, and the age range 18-24. The present analyses extend the classes and years to 1986, and the age range to 18-28. The years from 1976 through 1986 witnessed a variety of changes in the drug scene, as we have been reporting (Johnston, O'Malley, & Bachman, 1987a). Thus, the relatively simple findings reported in those earlier analyses have been made more complex by the passage of time, the addition of older ages, and the inclusion of more recent class cohorts. Nevertheless, the basic findings reported here are in most respects similar to the earlier findings. Table D summarizes the findings; Tables 1-18 show observed and estimated prevalences, as well as specific model information for all drug measures, and Figures 1-18 display the observed prevalences.

Cigarettes

Each of the figures shows the longitudinal trajectories for the classes of 1976-1986, followed up through 1986; Figures 1, 2, and 3 show the percentages smoking cigarettes at three different levels (monthly, daily, and 1/2 pack or more per day). Figure 3 is perhaps the clearest, and we discuss it first. The top line of connected open circles shows that the percentage from the class of 1976 smoking cigarettes at the rate of 1/2 pack or more per day was 19 percent in senior year, rose to 24 percent the following year, and continued at just about that level through 1986, when the modal age was 24. Note in Figure 3 that smoking among seniors had been showing declines between 1977 and 1981, with relatively little further change since then (see the left-most point on each line). In the absence of the follow-up data, the decline observed between 1977 and 1981 could have been attributed to either a class effect (with members of each successive class having fewer smokers than the previous class), or a period effect (that is, fewer smokers each year, regardless of class or age).

The data displayed in Figure 3 (and tabulated in Table 3) suggest strongly that there was no period effect, but rather there was a clear class effect. Note that although the senior year data show declines for successive classes of seniors, the various classes do not show corresponding declines in the follow-up data, as would occur if there were period effects. This finding is consistent with our earlier interpretation of the change as reflecting a class effect, based on retrospective data covering the age band from sixth grade to twelfth grade (Johnston, Bachman,

[7]The non-variation for a measure is applicable to the table as a whole, including both base-year and follow-up data. For base-year only data, because of the much larger numbers of cases and the attendant smaller sampling errors, subtle shifts can be reliably discerned. Thus, although heroin use shows little overall change in the data presented here, there is a slight downward trend evident in the base-year data (Johnston, O'Malley, & Bachman, 1987a).

& O'Malley, 1982). In addition to the class effect, there is also an evident age effect; all classes show a jump in the percentages smoking 1/2 pack or more per day in the first three years after high school.

Row three of Table D provides a quantitative summary of the pattern described above. The entry in the "Constant-only" column of the table indicates a very low probability (zero, to three decimal places) that a constant-only model could adequately describe the data. The fitted model reproduces the observed data quite well; the nominal probability that the model could have generated the observed data is .998, and 90.5% of the variation around a constant-only model is accounted for. The other entries in the third row of Table D can be interpreted as follows. The constant is 20.4%, which means that the predicted value for smoking 1/2 pack or more per day for the first data point -- the class of 1976 surveyed in 1976 -- is 20.4%. There is a linear class effect of -1.0%, so that each successive class is predicted to have 1.0% fewer of such smokers than the preceding class. There is no period effect at all, but there is a nonsimple linear age effect that indicates an increase of 1.7% per year of age in rates of half-a-pack or more smoking between ages 18 and 21, with no further age-related changes after age 21.

Thus, the *estimated* or predicted, value for the class of 1980 followed up in 1986 would be:

$$=20.4\% + 3(1.7\%) + 4(-1.0\%) = 21.5\%.$$

There are three increments of 1.7%, one for each year of age from 18 to 21 (19, 20, and 21), four decrements of 1.0%, one for each class after 1976 (1977, 1978, 1979, and 1980).

The actual observed value, as shown in Table 3, is 22.4%; thus there is an error, or residual, of 0.9%.

The other measures of cigarette use show very similar class effects, but slightly different age effects. For monthly cigarette use (that is, smoking at least one cigarette in the prior 30 days), use increases linearly, and modestly, until the age of approximately 21, after which use declines modestly (Figure 1 and Table 1).

The measure of daily use of cigarettes (that is, smoking at least one cigarette per day in the prior 30 days) shows a jump of almost 3% in just the first year after high school graduation, with no further consistent increase (Figure 2 and Table 2).

Taken together, these three measures indicate that cigarette use is declining with successive cohorts, but that users tend to increase their use after high school. Another way to view the monthly use results is to take the complement: that is, nonsmoking rates. These decline modestly in the first 2-3 years after high school, and then increase. The prevalence of heavier use (particularly 1/2 pack or more per day) shows some early increase, followed by no decline, at least through age 28 in these data. This pattern suggests that a very few individuals may start smoking in the first few years after high school, but that practically no one starts after age 21.

The class, or cohort, effect, is now estimated at about -1.0% for all three measures, compared to about -1.5% in the earlier analysis. The more recent cohorts have not been evidencing as much of a difference from class to class as the earlier cohorts did, and the slope of the overall linear

regression line for all cohorts is now only two-thirds as steep. In fact, a close inspection indicates that a more complicated class effect would fit the data for all three measures slightly better than the simple linear effect, although the already very good fits preclude any great improvement. The nature of the more complicated effect is that, although the overall average decline is approximately 1% per class (as shown in Table D), the earlier classes of 1976 through 1980 were declining at about 1.5% per class, whereas the later classes of 1981-1986 have been declining much more slowly (at about 0.4% per class for the entire interval). Indeed, the very recent cohorts of 1984-1986 may be declining still more slowly, or not at all; it is more difficult to estimate precisely a cohort effect for the recent cohorts because there are only a few data points available. For example, the cohort of 1986 provides only one data point, and the cohort of 1985 only two points.

We believe that the decline in successive classes is likely due, at least in part, to the increased concern in recent years about the harmful health consequences of smoking and to the increased generally negative attitudes toward public smoking. The lower rate of decline, and perhaps leveling, in the most recent classes may reflect the impact of greatly increased promotion and advertising of cigarettes since the ban on electronic media advertising went into effect in 1971 (Cummins, 1984). Given the generally negative climate toward smoking, why is there not a general period effect? The data suggest that cigarette smoking is very resistant to change; once it reaches the daily level, the behavior is likely to continue, and thus we see continuing differences between classes.

We noted that the age effects differed for the three smoking measures, and were not simple linear effects. In fact, as indicated in Table D, the majority of age and year effects across all drugs are not linear. In all but one case, these represent some combination of linear changes and intervals with no change (for example, a linear age effect through age 21 and constant thereafter.) (The one exception is for methaqualone (Quaaludes), where the year effect is mixed.) The general lack of simplicity is not surprising, given the volatility of substance use in recent years, and the considerable developmental changes that individuals go through between the age of 18 and 28. These relatively complex results are more evident now than they were in the earlier reported analyses, due to the continued volatility of substance use, the considerable amount of developmental changes, and also to the simple fact that there are more data points, particularly for the older age groups, which helps to make clearer what effects seem most likely to be operating.

Alcohol

The strongest effects for the various alcohol use measures are age effects, as we found also in the earlier report (Figures 4-6 and Tables 4-6). These strong age effects are understandable, given that most respondents are below the minimum drinking age at ages 18-20 and all are at or above the minimum age thereafter. However, the age effects are not identical across measures, and they certainly do not reflect a sudden increase in drinking behavior at age 21, when most respondents reach the legal minimum age. For all three measures (monthly prevalence, daily prevalence, and occasions of heavy use), the age effects reflect linear increases per year through age 21; the monthly and daily use show no further change thereafter, whereas the prevalence of occasions of heavy drinking declines. For the monthly measure, the increase through age 21 is 3.1% for each year of age, with a corresponding increase of 0.5% for daily use. For the measure of occasions of heavy drinking, the age effect similarly reflects an increase through age 21 (1.8%

per year of age), but then shows a linear decline (again of 1.8% per year of age). The earlier analyses had not been so clear in showing age 21 as a transition point, and we stated in the 1984 report that a few more years of data would help to show just where a peak in frequent heavy drinking occurs. It appears now that the peak is right around age 21, which is fairly consistent with results of another longitudinal study that found that periods of highest use of alcohol occurred between ages 18 and 20 (Kandel & Logan, 1984).

In addition to the age effects there are now some modest secular trends evident for the monthly and "heavy" alcohol use measures, trends that had not been clear in the earlier report. Both have shown linear declines since 1979, of 0.5% to 0.6% per year. Monthly use was essentially constant prior to 1979, while occasions of heavy drinking had been increasing. (Annual use of alcohol is not included here because it was essentially invariant across year, age, and cohort, with prevalence rates at about 90%.)

Marijuana

Unlike alcohol, the use of marijuana had shown a strong secular trend earlier, increasing from 1976 through 1979 and decreasing thereafter at approximately the same rate. This secular trend continues to be true through 1986 (Figures 7-9 and Tables 7-9). All three measures—annual, monthly, and daily—show "bilinear" effects, that is, a period of linear increases followed by a period of linear decreases (of equal size), and these effects describe the observed data fairly well. This strong secular trend was the most dominant effect in the earlier report, but there was a slight positive linear age or negative linear class effect with respect to daily use; the two effects were about equally likely, but we reported the age effect because of our prior assumptions that age effects were more likely than class effects. With the extended data, that effect now appears more likely to be a class effect, as we indicate in Table 9 (-0.2% per class); a corresponding age effect fits the data less well, albeit only slightly so. On the other hand, both the annual and monthly use measures now show slight bilinear age effects, increasing through age 21 or 22 and declining thereafter, which is very similar to the age effect for the measure of heavy drinking. Kandel and Logan (1984) had reported a maturational trend in marijuana use, with a decline beginning around age 22; our earlier data were somewhat ambiguous, due in part to few cases in the over-22 age group. The present extended dataset suggest that there is indeed a negative age effect after about age 21 or 22, for annual and monthly marijuana use. As indicated earlier, however, the measure of daily use of marijuana does not show a similar peaking at around age 21-22 (controlling for the strong secular trend) (Figure 9). It continues to be true that the secular trend is clearly the strongest factor in accounting for changes in all measures of marijuana use.

Illicit Drugs Other than Marijuana

Annual *cocaine* use shows a complex pattern of use (Figure 10 and Table 10). Two effects are clearly present: an age effect and a period effect. The former reflects linear increases through age 21 (or 22), and constant thereafter;[8] the latter reflects linear increases from 1976 through about 1980, and constant thereafter.

The age effect is quite strong—on average, the data show an increase of 2.9% per year as respondents went from age 18 and 21 or 22 (controlling for the secular trend that occurred

[8]A peak at either age 21 or 22 represents the data about equally well.

between 1976 and 1980). These age related changes are much stronger for cocaine than for any of the other illicit drugs, including marijuana. In fact, marijuana is the only other illicit drug that shows an age-related increase (for annual and monthly use, to about age 21 or 22). The other illicits that show age-related changes all decrease—amphetamines, barbiturates, LSD, and narcotics other than heroin.

In addition to the strong age effect for cocaine use, there were period effects in the interval from 1976 to 1980, reflecting average increases of 1.7% per year (controlling for the age effect occurring between age 18 and 21).

The prevalence of annual cocaine use does not seem to have changed since about 1980; but there are other indications that the nature of use has changed in ways that suggest the problem has been increasing. Specifically, smoking of cocaine has increased (versus snorting or sniffing), and the recent upsurge of crack use (if one believes the media coverage) may change future trends (Johnston, O'Malley, and Bachman, 1987a).

Amphetamine use demonstrated the strongest year-related changes of all 18 measures, increasing at a rate of 2.7% per year from 1976 to 1981, then decreasing at the same rate from 1982 to 1986 (Figure and Table 11). As we have discussed at length elsewhere (Johnston, O'Malley, & Bachman, 1987a), part of this change is artifactual.

Prior to the 1982 survey we had discovered that, in their responses to questions on amphetamine use, some respondents were erroneously including their use of over-the-counter stay-awake and diet pills, as well as some "look-alike" pills. In the 1982 survey, we changed the wording of the question in order to make clear to the respondents that "look-alike" pills
and over-the-counter products containing stimulants should be excluded. The old versions of these questions were retained in two of the five forms in the base-year survey, but not in the follow-up surveys. Based on the comparison between the new and old versions in the senior-year data, there appear to be fewer respondents inappropriately reporting non-amphetamine use in the new versions of the questionnaires; thus, the change in prevalence appears due at least in part to the change in the questions. Although part of the secular trends is artifactual, it is clear that considerable real change has also occurred; since 1982 in fact, there has been a net average decrease of 2.7% per year. In addition, an inspection of residuals indicated a small age effect, with a 0.7% per year decline showing up after age 21.

Methaqualone, one of the two types of sedatives under study, provided the one instance in model-fitting where linear or constant effects were inadequate. During the period from 1976 to 1980 there was substantial change, but it was not very regular; hence, a series of dummy variables was required to represent change in this period. Since then, there have been steady declines of about 1.4% per year for all age groups (Figure 12 and Table 12). (Legal production and distribution of methaqualone have been discontinued in this country, but there continues to be illegal and imported quantities available.)

Barbiturates, the other type of sedative included in the study, have been declining through the period 1976-1986, at a rate of about 0.6% per year (Figure 13 and Table 13). (This represents, of course, a best-fit straight line, and doesn't mean that there has been a decline of exactly 0.6% every year. But, coupled with one age-related change, this model explains almost all of the

variance left unaccounted for by a constant.) One additional feature appeared to be indicated by an inspection of the residuals, and that is a decrease in the first year after high school of 1.9%.

The secular trend for *LSD* is similar to that for marijuana: increasing through 1979, and decreasing since (Figure 14 and Table 14); for LSD, the annual change has been 0.7%. There also appears to be a small age effect, with older ages successively slightly less likely (by 0.2%) to have used LSD in the prior year. This small effect is highly statistically significant (nominally speaking); the probability level of the simpler model is less than .02, compared to .69 for the model that includes the age effect. Because a bilinear year effect has already been fitted, a class effect would work as well (actually, the class effect is trivially better, $p = .74$), but as discussed earlier, we believe that age effects are more likely than class effects. Moreover, the age effect is much more consistent with the other findings illustrated in Table D.

Psychedelics other than LSD reflect a simpler pattern. They show a linear secular trend down, at the rate of 0.6% per year (Figure 15 and Table 15).

Tranquilizers show exactly the same pattern, down 0.6% per year (Figure 16 and Table 16). In this case, however, the model doesn't fit the data as well as most drugs. The fitted model has a nominal probability of .546, and only two-thirds of the error variance is accounted for. The residuals from this model indicate that either a positive linear age effect or a negative class effect would improve the fit. As discussed above, there is no way to choose between these two alternatives. Although we have generally preferred to give priority to an age effect, that alternative is less attractive here because none of the other psychotherapeutic drugs show positive age effects. Therefore, no age or class effect is shown. In any case, the estimated value of the excluded parameter value is quite small (0.2%) relative to the estimated year parameter (0.7% when an age or class effect is included, and 0.6% otherwise).

Heroin use was reported by very few respondents; a constant 0.2% "explains" the data very well (Figure 17 and Table 17). This comment is applicable to the table as a whole, including both base-year and follow-up data. For base-year only data, because of the much larger numbers of cases and the attendant smaller sampling errors, subtle shifts can be reliably discerned. Thus, although heroin use shows little overall change in the data presented here, there is a slight downward trend evident in the base-year data, particularly when data from the class of 1975 are included (Johnston, O'Malley, & Bachman, 1987a)

Finally, *narcotics other than heroin* is the only class of illicit drugs other than heroin to show no secular trend. There appears to be an age-linked decline, of about 0.3% per year (Figure 18 and Table 18). As with tranquilizers, there is considerable variance left unaccounted for, but there does not appear to be any simple pattern to the observed data.

Summary of Results

The data presented above display quite an impressive variety of change patterns observed among the different drugs in the relatively short interval between 1976 and 1986. Several kinds of *period* effects were evident. Monthly alcohol use was constant through 1979, decreasing thereafter. Cocaine use increased through 1980, with no change thereafter. Linear decreases occurred for barbiturates, psychedelics other than LSD, and tranquilizers. A bilinear period effect, first increasing and then decreasing, was observed for occasions of heavy drinking,

marijuana, amphetamines, and LSD. Quaaludes also increased and then decreased, though the increase was not linear in form.

Effects of *age* were also complex. Increases in the early years after high school were seen for all measures of cigarette use. The different patterns indicated that there was not much increase in the proportion who were active smokers in the years after high school, but that among those who smoked, a higher proportion became frequent smokers. Monthly and daily use of alcohol and annual prevalence of cocaine increased linearly with age through age 21 and were constant thereafter. A measure of occasions of heavy drinking showed a similar increase through age 21, but declined thereafter. Annual and monthly marijuana prevalence followed a similar pattern, peaking at age 21 or 22 and declining thereafter. Amphetamine use also declined with age after 21, but did not increase during the post-high school years. Annual use of LSD and narcotics other than heroin showed simple linear age decreases.

Clear *class* effects appeared for cigarette use, with successive classes smoking less at all levels. Similarly, daily marijuana use seems to declining with successive classes.

DISCUSSION

The period effects reported in the results section are generally quite consistent with our previous reports based on senior year data only (Johnston, O'Malley, & Bachman, 1987a). For example, marijuana use had been increasing and more recently has been decreasing, and we interpreted this as a general curvilinear period effect. Cigarette use among seniors showed a pattern similar to marijuana—an early increase followed by a decrease (although the decrease did not continue as was the case for marijuana). The cohort-sequential design permits a different, and we believe more accurate, interpretation of the cigarette use pattern as being a class effect, rather than a period effect. Clearly, the cohort-sequential design is of critical importance in helping to make proper interpretations of the role of period, age, and class.

We do not wish to imply that the interpretations that we have made are indisputable. They are our conclusions, based on the patterns reflected in the observed data, subject to criteria of reasonable and parsimonious effects. Unfortunately, however, there are situations in which the most parsimonious explanation is likely to be incorrect; Glenn (1981) provided one such example, using data from national surveys on drinking of alcoholic beverages between 1956 and 1977. Although the data appeared to present a tidy pattern explainable by a pure linear cohort effect, consideration of additional information led Glenn to conclude that the observed pattern more likely arose from two off-setting types of effects—a positive period effect, and a negative aging effect. The inference to be drawn is, again, that the separation of cohort, period, and age effects is not at all a straight-forward enterprise. Considerable deliberation of a non-statistical nature is critically important in the interpretation of results.

Throughout this report we have been using the terms "year effect," "age effect," and "class effect." But we do not attribute any *causal* interpretation to year, or age, or class. Year, or time, is actually a proxy for, as Duncan put it, "a collection of indirectly observed causal factors" (1981, p. 282). These not-directly-observed factors are all the things that change over time in the physical or social environment and that may be important. They range from very basic and obvious factors such as availability (a very important long-term historical factor in illicit drug

use) to more subtle factors such as the connotations of drug use (for example, is such use accepted or admired—particularly by peers—or is it regarded with disdain?).

Age effects also encompass a very broad range of possible underlying causes. For example, legal sanctions may have an important influence on behavior. Many behaviors are age-regulated (voting, driving, marrying), and "age" per se ought to have an effect on such behaviors. Purchase of alcohol is age-regulated, and we do observe an age effect on alcohol use; the effect falls short of being dramatic at least in part because legal restrictions are far from completely effective in suppressing under-age use.

There are also consistent biological changes associated with aging, as well as some important transitions in social roles. The latter are especially important for the age span under study here, with all the major transitions that occur between adolescence and adulthood. One important social role transition is graduation from high school, and we see a particularly strong effect of this transition on the frequency of cigarette use. Other important role transitions that typically occur during the years after high school graduation include becoming a full-time worker, moving out of the parental home (possibly to go to college, to enter military service, or to marry and set up an independent living situation), and becoming a parent.

Some of these transitions would be expected to lead to a decrease in drug use. For example, marriage seems to be accompanied by a decrease in use of alcohol and illicit drugs (Bachman, O'Malley, & Johnston, 1978; Bachman, O'Malley, & Johnston, 1981, 1984; Donovan, Jessor, & Jessor, 1983). Other things equal, these decreases would result in a negative relationship between drug use and age. Of course, other things are not equal; many other transitions are occurring. One of these other transitions is that some young people move out of the parental home, and live alone or with others of similar ages. For those who do not marry, this transition seems to be associated with an increase in use of alcohol and illicit drugs, and these increases would lead to a positive relationship between age and drug use. In the Monitoring the Future dataset, the latter relationships are apparently somewhat stronger than those producing a negative relationship, and age effects are generally positive (though the relationships are complex, as illustrated in Table D).

Class, or cohort, effects are somewhat less straightforward in their interpretations. In one sense, they are interactions between year (or period) effects and age effects; that is, they are period effects that affect only some age groups.[9] For example, cohorts that were of wage-earning age during the Great Depression of the 1930s are hypothesized to have been affected differently than other cohorts. But the Great Depression itself was clearly a period phenomenon—the decade of the 1930s. Another example: the "baby boom" cohorts were originally produced by the period effect or effects connected with the end of World War II. The necessary condition for a cohort effect is that the impact of some period effect has a *permanent* effect on particular cohorts. For those who live through military or economic crises, the "scars" take the form of memories,

[9]It should be made clear that, while class or cohort effects may be thought of as interactions between time and age, cohort effects are not necessarily interactions in the statistical sense. Linear age, cohort, and year effects will not appear as interactions detectable by statistical tests for interaction (Glenn, 1977, p. 58).

cognitions, and attitudes that may last a lifetime. For individuals in a cohort with particular demographic characteristics, those very characteristics may have enduring effects, such as the crowding for jobs and education opportunities experienced by those born late in the baby boom.

In the current study, cohort (class) effects are most clear in the case of cigarette use. Medical evidence of the long-term negative physical effects of smoking became increasingly clear and salient during the 1970s, as new and more damaging evidence was accumulated and publicized. While such evidence was available to the entire population, it likely was particularly effective with non-smokers. That is, the new information probably was more helpful in preventing the initiation of smoking than in prompting cessation. Of course, this may be due largely to the fact that cigarette use is, for many people, an addictive behavior, unlike much of the other drug use discussed here; once started, it is very difficult to stop. Our findings, reported elsewhere, on the emergence of these cohort differences in smoking during early adolescence help to buttress this conclusion, along with the increasing reports by seniors of health concerns (Johnston, O'Malley, & Bachman, 1987a). Between 1979 and 1986, there was also considerable increase in the perceived risk associated with regular marijuana use, and this was associated with a period effect—all age groups showed declines in regular marijuana use. Apparently, this different outcome is because regular marijuana use is a more changeable behavior than regular cigarette use. (In addition to the addictive nature of cigarette use, there is also the presence of considerable promotion of cigarette use by the tobacco industry.)

The documentation of these various effects by use of a cohort-sequential design is but an early step in the scientific process. It provides a more refined description of a phenomenon, by separating observed changes into several qualitatively different component parts. The next step is the explanation of those component parts, and this requires an analysis of the collection of causal factors for which year, age, and class are proxies. Thus, one of the more interesting next steps is to disaggregate the data further. For example, we have already learned that age-linked effects are different for young adults living with a spouse, those still living with their parents, and those in other living arrangements (Bachman, O'Malley, & Johnston, 1981, 1984). We have also reported evidence suggesting that class effects for cigarette use may differ between males and females (Johnston, Bachman, & O'Malley, 1982). In future analyses employing the cohort-sequential design, we expect further refinements in sorting out year, age, and class effects; but of more importance will be continued efforts to understand the underlying causes.

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Table A

Cohort-Sequential Design

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	**18**	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*
1977		**18**	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*
1978			**18**	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*
1979				**18**	*19*	*20*	*21*	*22*	*23*	*24*	*25*
1980					**18**	*19*	*20*	*21*	*22*	*23*	*24*
1981						**18**	*19*	*20*	*21*	*22*	*23*
1982							**18**	*19*	*20*	*21*	*22*
1983								**18**	*19*	*20*	*21*
1984									**18**	*19*	*20*
1985										**18**	*19*
1986											**18**

Note:

Entries are modal ages; bold entries indicate base-year data collections, and entries in italics indicate follow-up data collections.

Table B

Hypothetical Data Showing "Pure" Linear Effects

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1. Age Effects											
1976	.10	.12	.14	.16	.18	.20	.22	.24	.26	.28	.30
1977		.10	.12	.14	.16	.18	.20	.22	.24	.26	.28
1978			.10	.12	.14	.16	.18	.20	.22	.24	.26
1979				.10	.12	.14	.16	.18	.20	.22	.24
1980					.10	.12	.14	.16	.18	.20	.22
1981						.10	.12	.14	.16	.18	.20
1982							.10	.12	.14	.16	.18
1983								.10	.12	.14	.16
1984									.10	.12	.14
1985										.10	.12
1986											.10
2. Year Effects											
1976	.10	.12	.14	.16	.18	.20	.22	.24	.26	.28	.30
1977		.12	.14	.16	.18	.20	.22	.24	.26	.28	.30
1978			.14	.16	.18	.20	.22	.24	.26	.28	.30
1979				.16	.18	.20	.22	.24	.26	.28	.30
1980					.18	.20	.22	.24	.26	.28	.30
1981						.20	.22	.24	.26	.28	.30
1982							.22	.24	.26	.28	.30
1983								.24	.26	.28	.30
1984									.26	.28	.30
1985										.28	.30
1986											.30
3. Class Effects											
1976	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
1977		.12	.12	.12	.12	.12	.12	.12	.12	.12	.12
1978			.14	.14	.14	.14	.14	.14	.14	.14	.14
1979				.16	.16	.16	.16	.16	.16	.16	.16
1980					.18	.18	.18	.18	.18	.18	.18
1981						.20	.20	.20	.20	.20	.20
1982							.22	.22	.22	.22	.22
1983								.24	.24	.24	.24
1984									.26	.26	.26
1985										.28	.28
1986											.30

Table C

Follow-Up Response Rates

Class	Year of Follow-Up Administration									
	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	63.4	81.5	77.1	82.5	77.6	80.4	77.6	74.8	73.0	75.0
1977		86.1	83.7	82.8	82.1	80.6	80.5	75.1	76.5	75.1
1978			85.0	84.9	82.3	81.8	81.2	77.8	75.0	76.7
1979				88.2	82.6	83.3	78.3	78.4	73.6	79.4
1980					87.3	84.6	82.7	78.2	77.7	78.8
1981						84.6	83.8	80.5	76.3	79.8
1982							84.3	83.4	78.2	78.6
1983								83.1	79.8	79.9
1984									78.5	82.3
1985										80.6

Notes:

Table entries are percentages, weighted response rates.

From each senior class, 2,400 cases (unweighted) are selected for follow-up; a random half (1,200) are followed in even-numbered years, and the other half (1,200) are followed in odd-numbered years. Weights are used because drug users are over-sampled, and they therefore need to be "down-weighted" in analyses. The weights average about .75, so the average weighted n per class per follow-up year is 900 (1200 x .75). A response rate of 80% would result in approximately 720 weighted cases (1200 x .75 x .80), or 960 actual unweighted cases (1200 x .80).

Table D
Summary Table of Effects

Prevalence Measure	Significant Effects (Entries are percents)				Probability of Model		Percent Error Reduction
	Constant	Year	Age	Class	Constant Only	Fitted Model	
1. Monthly Cigarettes	36.4		0.9[1]	−1.0	.000	.989	71.3
2. Daily Cigarettes (any)	28.3		+2.8[2]	−1.1	.000	.999	86.5
3. Daily Cigarettes(1/2pack)	20.4		+1.7[3]	−1.0	.000	.998	90.5
4. Monthly Alcohol	71.8	−0.5[4]	+3.1[3]		.000	.795	78.5
5. Daily Alcohol	5.7		+0.5[3]		.134	.768	28.6
6. 2 Weeks Alcohol 5+Drinks	38.8	0.6[5]	1.8[1]		.000	.950	79.9
7. Annual Marijuana	44.5	2.0[5]	1.2[1]		.000	.998	91.9
8. Monthly Marijuana	30.4	2.3[5]	0.4[6]		.000	.939	90.7
9. Daily Marijuana	8.2	0.8[5]		−0.2	.000	.980	85.3
10. Annual Cocaine	5.3	+1.7[7]	+2.9[3]		.000	.990	93.3
11. Annual Amphetamines	12.4	2.7[8]	−0.7[9]		.000	.880	92.4
12. Annual Methaqualone	9.1	−1.4[10]			.000	.918	92.3
13. Annual Barbiturates	9.3	−0.6	−1.9[2]		.000	.995	86.1
14. Annual LSD	6.4	0.7[5]	−0.2		.000	.690	84.5
15. Annual Psychedelics	8.2	−0.6			.000	.810	79.4
16. Annual Tranquilizers	10.7	−0.6			.000	.546	66.4
17. Annual Heroin	0.2				.902	.902	0.0
18. Annual Narcotics	5.0		−0.3		.000	.720	52.7

Notes:
[1]Age: Bilinear − increasing 18–21, and decreasing 22–28.
[2]Age: 18 ≠ 19–24.
[3]Age: Increasing to 21, constant thereafter.
[4]Year: Constant to 1979, decreasing thereafter.
[5]Year: Bilinear − increasing 1976–1979, and decreasing 1980–1986.
[6]Age: Increasing 18–22, and decreasing 23–28.
[7]Year: Increasing to 1980, constant thereafter.
[8]Year: Bilinear − increasing 1976–1981, and decreasing 1982–1986.
[9]Age: Constant to 21, decreasing thereafter.
[10]Year: Unconstrained 1976–1980, decreasing thereafter. (Table entry is for linear portion, 1981–1986.)

Table 1

Cigarettes: Monthly Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	38.8	39.3	39.0	40.5	35.7	38.6	38.0	36.7	33.0	34.1	33.1
Residual	*2.4*	*2.0*	*0.8*	*1.5*	*-2.4*	*1.3*	*1.5*	*1.2*	*-1.7*	*0.3*	*0.2*
1977		38.4	37.2	39.2	38.3	36.3	35.4	35.6	33.4	35.6	31.1
Residual		*2.9*	*0.9*	*2.0*	*0.3*	*-0.9*	*-1.0*	*0.1*	*-1.2*	*1.9*	*-1.7*
1978			36.7	39.4	39.4	37.1	37.0	35.4	34.6	33.0	31.2
Residual			*2.2*	*4.0*	*3.1*	*0.0*	*0.7*	*0.0*	*0.1*	*-0.6*	*-1.6*
1979				34.4	33.6	36.4	35.5	35.2	32.3	32.8	31.0
Residual				*0.8*	*-0.8*	*1.1*	*-0.6*	*-0.1*	*-2.2*	*-0.7*	*-1.7*
1980					30.5	33.8	31.0	33.0	31.1	31.3	29.0
Residual					*-2.1*	*0.3*	*-3.4*	*-2.2*	*-3.3*	*-2.1*	*-3.6*
1981						29.4	33.0	33.2	33.8	32.8	31.2
Residual						*-2.3*	*0.5*	*-0.2*	*-0.4*	*-0.6*	*-1.4*
1982							30.0	32.4	33.7	31.8	31.6
Residual							*-0.7*	*0.9*	*1.3*	*-1.5*	*-0.9*
1983								30.3	30.3	31.1	33.0
Residual								*0.6*	*-0.3*	*-0.4*	*0.7*
1984									29.3	31.4	30.6
Residual									*0.6*	*1.7*	*0.1*
1985										30.1	30.6
Residual										*2.3*	*1.9*
1986											29.6
Residual											*2.7*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 40.11 with 63 degrees of freedom, P = .989.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	36.4
Age (Bilinear, up to 21, then down)	0.9
Class	−1.0

Table 2

Cigarettes: Daily Prevalence (Any)

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	28.8	30.5	32.6	31.8	31.3	31.2	31.7	30.5	29.2	28.1	29.1
Residual	*0.5*	*-0.6*	*1.6*	*0.7*	*0.2*	*0.1*	*0.7*	*-0.6*	*-1.9*	*-3.0*	*-2.0*
1977		28.8	30.1	32.0	31.9	33.2	30.1	31.0	29.4	31.6	27.3
Residual		*1.6*	*0.1*	*2.0*	*1.9*	*3.2*	*0.1*	*1.0*	*-0.6*	*1.6*	*-2.7*
1978			27.5	31.5	31.3	30.0	29.7	30.5	29.2	29.9	27.7
Residual			*1.4*	*2.6*	*2.4*	*1.1*	*0.8*	*1.6*	*0.3*	*1.0*	*-1.1*
1979				25.4	28.5	27.6	27.9	28.6	26.6	27.3	27.3
Residual				*0.4*	*0.8*	*-0.2*	*0.1*	*0.8*	*-1.1*	*-0.5*	*-0.4*
1980					21.4	24.9	24.9	24.9	25.4	24.6	25.3
Residual					*-2.5*	*-1.8*	*-1.8*	*-1.8*	*-1.3*	*-2.1*	*-1.4*
1981						20.3	23.1	25.5	26.1	25.4	25.5
Residual						*-2.5*	*-2.5*	*-0.1*	*0.5*	*-0.2*	*-0.1*
1982							21.1	23.9	26.1	25.6	25.3
Residual							*-0.6*	*-0.6*	*1.6*	*1.1*	*0.8*
1983								21.2	22.8	24.8	24.4
Residual								*0.6*	*-0.6*	*1.4*	*1.0*
1984									18.7	21.7	23.3
Residual									*-0.8*	*-0.6*	*1.0*
1985										19.5	21.5
Residual										*1.1*	*0.2*
1986											18.7
Residual											*1.4*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 32.87 with 63 degrees of freedom, P = .999.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	28.3
Age(18 ≠ 19–24)	2.8
Class	−1.1

Table 3

Cigarettes: Daily Prevalence (1/2 Pack a day)

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	19.2	24.0	24.8	26.9	25.2	25.9	26.2	25.0	23.6	26.1	23.9
Residual	*-1.2*	*1.9*	*1.1*	*1.5*	*-0.2*	*0.5*	*0.8*	*-0.4*	*-1.8*	*0.7*	*-1.5*
1977		19.4	22.8	24.9	24.9	25.4	23.8	24.6	24.9	24.2	23.1
Residual		*-0.1*	*1.7*	*2.2*	*0.5*	*1.0*	*-0.6*	*0.2*	*0.5*	*-0.2*	*-1.3*
1978			18.8	24.1	23.0	24.5	24.4	24.5	23.6	24.4	20.9
Residual			*0.3*	*3.9*	*1.2*	*1.0*	*1.0*	*1.1*	*0.2*	*0.9*	*-2.6*
1979				16.5	21.3	19.6	21.7	21.9	22.1	21.9	23.2
Residual				*-1.0*	*2.2*	*-1.2*	*-0.8*	*-0.6*	*-0.4*	*-0.6*	*0.7*
1980					14.3	17.2	19.3	17.2	21.8	19.3	22.4
Residual					*-2.3*	*-1.0*	*-0.6*	*-4.3*	*0.3*	*-2.3*	*0.9*
1981						13.5	17.3	18.6	21.5	20.2	20.9
Residual						*-2.1*	*0.0*	*-0.3*	*0.9*	*-0.4*	*0.3*
1982							14.2	15.5	17.8	20.1	19.1
Residual							*-0.5*	*-0.8*	*-0.2*	*0.5*	*-0.6*
1983								13.8	16.2	19.0	18.8
Residual								*0.1*	*0.9*	*2.0*	*0.2*
1984									12.3	13.7	17.6
Residual									*-0.4*	*-0.7*	*1.6*
1985										12.5	14.7
Residual										*0.7*	*1.3*
1986											11.4
Residual											*0.6*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 35.66 with 63 degrees of freedom, P = .998.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	20.4
Age (up to 21, constant thereafter)	1.7
Class	−1.0

Table 4

Alcohol: Monthly Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	68.3	72.4	76.8	76.9	77.3	79.2	78.0	76.1	76.3	76.5	73.2
Residual	*-3.5*	*-2.5*	*-1.2*	*-4.2*	*-3.3*	*-0.9*	*-1.5*	*-2.9*	*-2.1*	*-1.4*	*-4.2*
1977		71.2	76.5	77.1	81.7	81.1	81.0	78.8	77.7	76.9	77.1
Residual		*-0.6*	*1.6*	*-1.0*	*1.1*	*1.0*	*1.5*	*-0.2*	*-0.7*	*-1.1*	*-0.3*
1978			72.1	76.2	78.5	79.7	79.8	79.2	78.4	77.2	77.6
Residual			*0.3*	*1.3*	*1.0*	*-0.4*	*0.2*	*0.2*	*-0.1*	*-0.7*	*0.1*
1979				71.8	76.8	78.8	81.7	79.7	78.6	81.5	76.3
Residual				*0.0*	*2.4*	*1.8*	*2.1*	*0.7*	*0.1*	*3.6*	*-1.2*
1980					72.0	77.0	78.2	80.6	81.1	79.7	77.2
Residual					*0.7*	*3.2*	*1.8*	*1.6*	*2.6*	*1.8*	*-0.2*
1981						70.7	74.8	76.9	77.4	78.6	76.8
Residual						*0.0*	*1.5*	*1.0*	*-1.1*	*0.6*	*-0.6*
1982							69.7	73.2	75.6	75.7	78.2
Residual							*-0.5*	*0.4*	*0.2*	*-2.2*	*0.7*
1983								69.4	73.2	77.6	77.8
Residual								*-0.3*	*0.9*	*2.8*	*0.4*
1984									67.2	72.6	75.4
Residual									*-2.0*	*0.9*	*1.1*
1985										65.9	71.0
Residual										*-2.7*	*-0.2*
1986											65.3
Residual											*-2.8*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 53.61 with 63 degrees of freedom, P = .795.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	71.8
Year (constant to 1979, down thereafter)	−0.5
Age (up to 21, constant thereafter)	3.1

Table 5

Alcohol: Daily Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	5.6	5.8	8.1	10.0	9.2	8.5	8.6	6.6	7.7	7.3	7.6
Residual	*-0.1*	*-0.3*	*1.3*	*2.7*	*1.9*	*1.2*	*1.4*	*-0.7*	*0.4*	*0.0*	*0.4*
1977		6.1	7.7	8.6	8.4	7.0	8.1	8.1	6.7	7.5	7.1
Residual		*0.4*	*1.5*	*1.9*	*1.2*	*-0.3*	*0.8*	*0.8*	*-0.5*	*0.2*	*-0.2*
1978			5.7	7.9	7.0	8.3	6.9	8.5	6.7	6.7	4.9
Residual			*0.0*	*1.7*	*0.3*	*1.0*	*-0.4*	*1.2*	*-0.6*	*-0.6*	*-2.4*
1979				6.9	8.6	8.3	8.6	8.8	7.0	7.5	6.1
Residual				*1.2*	*2.4*	*1.6*	*1.4*	*1.5*	*-0.2*	*0.2*	*-1.2*
1980					6.0	6.1	7.4	7.4	8.4	6.8	6.5
Residual					*0.3*	*-0.1*	*0.7*	*0.1*	*1.1*	*-0.4*	*-0.7*
1981						6.0	7.7	5.5	7.5	6.4	5.9
Residual						*0.3*	*1.5*	*-1.2*	*0.2*	*-0.8*	*-1.3*
1982							5.7	5.3	5.9	6.2	6.0
Residual							*0.1*	*-0.8*	*-0.8*	*-1.0*	*-1.2*
1983								5.5	5.4	5.8	6.8
Residual								*-0.2*	*-0.7*	*-0.9*	*-0.5*
1984									4.8	5.2	5.3
Residual									*-0.8*	*-0.9*	*-1.4*
1985										5.0	5.2
Residual										*-0.7*	*-0.9*
1986											4.8
Residual											*-0.9*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 55.45 with 64 degrees of freedom, P = .768.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	5.7
Age (up to 21, constant thereafter)	0.5

Table 6

Alcohol: 2 Weeks Prevalence (5+ drinks)

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	37.1	39.4	41.6	42.6	42.3	42.6	37.0	34.6	32.7	31.9	29.6
Residual	*-1.7*	*-1.8*	*-2.1*	*-3.5*	*-1.4*	*1.4*	*-1.7*	*-1.7*	*-1.2*	*0.4*	*0.6*
1977		39.4	44.1	44.7	43.9	41.2	40.4	37.8	36.7	32.6	32.0
Residual		*0.0*	*2.3*	*0.5*	*-1.6*	*-1.9*	*-0.3*	*-0.3*	*0.9*	*-0.7*	*1.1*
1978			40.3	42.5	45.7	45.6	41.0	40.7	33.1	34.6	29.8
Residual			*0.3*	*0.1*	*2.1*	*0.7*	*-1.5*	*0.7*	*-4.5*	*-0.5*	*-3.0*
1979				41.2	43.1	44.6	43.1	43.4	36.7	37.1	32.8
Residual				*0.7*	*1.3*	*1.5*	*-1.2*	*1.6*	*-2.8*	*0.1*	*-1.8*
1980					41.2	42.0	41.2	41.8	41.7	37.3	36.0
Residual					*1.2*	*0.8*	*-1.2*	*-1.9*	*0.4*	*-1.6*	*-0.4*
1981						41.4	44.5	45.1	41.7	43.1	36.6
Residual						*2.0*	*3.9*	*3.2*	*-1.4*	*2.4*	*-1.7*
1982							40.5	38.4	43.4	38.9	40.5
Residual							*1.8*	*-1.6*	*2.1*	*-3.7*	*0.4*
1983								40.8	40.9	42.1	43.4
Residual								*2.6*	*1.4*	*1.4*	*1.4*
1984									38.7	42.5	42.2
Residual									*1.1*	*3.7*	*2.1*
1985										36.7	40.8
Residual										*-0.3*	*2.6*
1986											36.8
Residual											*0.4*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 45.76 with 63 degrees of freedom, P = .950.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	38.8
Year (up to 1979, down thereafter)	0.6
Age (up to 21, down thereafter)	1.8

Table 7

Marijuana: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	44.5	48.4	53.2	52.4	49.4	45.7	45.0	39.3	35.5	33.2	31.2
Residual	*0.0*	*0.7*	*2.2*	*-1.8*	*-1.6*	*-2.1*	*0.5*	*-2.0*	*-2.5*	*-1.6*	*-0.3*
1977		47.6	53.8	52.0	52.2	51.8	47.3	42.4	40.2	37.9	32.5
Residual		*1.1*	*4.0*	*-1.0*	*0.0*	*2.8*	*1.6*	*-0.1*	*0.9*	*1.9*	*-0.3*
1978			50.2	51.5	50.2	50.6	44.1	44.4	36.3	40.7	31.7
Residual			*1.7*	*-0.3*	*-0.7*	*0.4*	*-2.8*	*0.7*	*-4.2*	*3.5*	*-2.3*
1979				50.8	50.1	51.6	47.7	46.1	41.2	42.4	36.6
Residual				*0.2*	*0.3*	*2.6*	*-0.5*	*1.1*	*-0.5*	*4.0*	*1.3*
1980					48.8	47.8	45.1	45.3	41.9	40.9	36.0
Residual					*0.3*	*0.0*	*-1.8*	*-0.9*	*-1.0*	*1.2*	*-0.5*
1981						46.1	45.0	44.4	43.0	40.0	36.3
Residual						*-0.4*	*-0.7*	*-0.5*	*-1.1*	*-0.9*	*-1.4*
1982							44.3	41.5	41.9	42.3	38.1
Residual							*-0.2*	*-2.2*	*-1.1*	*0.2*	*-0.9*
1983								42.3	40.8	42.0	41.5
Residual								*-0.2*	*-0.9*	*1.0*	*1.4*
1984									40.0	38.9	39.5
Residual									*-0.5*	*-0.9*	*0.6*
1985										40.6	39.2
Residual										*2.1*	*1.5*
1986											38.8
Residual											*2.3*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 35.49 with 63 degrees of freedom, P = .998.

Fitted model (all effects iinear except as noted):

Effect	Parameter
Constant	44.5
Year (up to 1979, down thereafter)	2.0
Age (up to 21, down thereafter)	1.2

Table 8

Marijuana: Monthly Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976 .	32.2	35.8	38.3	38.6	37.9	33.4	30.9	27.0	23.6	24.1	20.8
Residual	*1.8*	*2.7*	*2.4*	*-0.1*	*1.0*	*-0.6*	*-0.3*	*-1.4*	*-2.0*	*1.2*	*0.7*
1977 .		35.4	38.6	41.4	36.1	37.9	30.1	29.1	25.2	25.7	20.1
Residual		*2.7*	*3.1*	*3.1*	*-0.3*	*3.4*	*-1.6*	*0.2*	*-0.9*	*2.4*	*-0.5*
1978 .			37.1	37.7	36.7	33.3	29.1	30.4	24.1	25.1	19.3
Residual			*2.0*	*-0.2*	*0.7*	*-0.7*	*-3.1*	*1.1*	*-2.5*	*1.4*	*-1.6*
1979 .				36.5	35.5	34.8	30.1	28.9	27.7	26.8	21.0
Residual				*-0.9*	*0.0*	*1.2*	*-1.6*	*-0.9*	*0.7*	*2.6*	*-0.4*
1980 .					33.7	33.0	29.2	28.9	27.0	25.2	22.7
Residual					*-1.4*	*-0.2*	*-2.1*	*-0.5*	*-0.4*	*0.6*	*0.9*
1981 .						31.6	28.6	27.0	27.1	25.3	23.3
Residual						*-1.1*	*-2.2*	*-1.9*	*0.1*	*0.2*	*1.0*
1982 .							28.5	23.6	26.0	24.7	24.1
Residual							*-1.9*	*-4.9*	*-0.6*	*0.0*	*1.4*
1983 .								27.0	24.5	24.6	23.0
Residual								*-1.0*	*-1.6*	*0.4*	*0.7*
1984 .									25.2	20.6	22.7
Residual									*-0.5*	*-3.1*	*0.8*
1985 .										25.7	22.1
Residual										*2.4*	*0.7*
1986 .											23.4
Residual											*2.4*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 46.65 with 63 degrees of freedom, P = .939.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	30.4
Year (up to 1979, down thereafter)	2.3
Age (up to 22, down thereafter)	0.4

Table 9

Marijuana: Daily Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	8.2	10.0	11.7	12.7	12.2	9.6	8.3	8.1	6.9	8.0	5.2
Residual	*0.0*	*1.0*	*1.9*	*2.1*	*2.4*	*0.6*	*0.1*	*0.6*	*0.2*	*2.2*	*0.2*
1977		9.1	10.1	11.6	10.1	10.4	7.2	6.8	4.9	6.2	4.1
Residual		*0.3*	*0.5*	*1.2*	*0.5*	*1.6*	*-0.7*	*-0.4*	*-1.5*	*0.6*	*-0.7*
1978			10.7	11.0	9.3	8.2	6.9	6.8	5.6	5.9	3.5
Residual			*1.3*	*0.8*	*0.0*	*-0.4*	*-0.9*	*-0.2*	*-0.6*	*0.5*	*-1.1*
1979				10.3	8.2	8.2	6.2	5.4	5.4	5.6	3.8
Residual				*0.4*	*-0.9*	*-0.1*	*-1.3*	*-1.3*	*-0.5*	*0.4*	*-0.5*
1980					9.1	6.9	6.9	6.3	5.0	5.4	4.8
Residual					*0.2*	*-1.2*	*-0.4*	*-0.2*	*-0.7*	*0.5*	*0.7*
1981						7.0	5.9	5.7	5.6	5.0	4.5
Residual						*-0.9*	*-1.1*	*-0.6*	*0.2*	*0.4*	*0.7*
1982							6.3	4.5	4.6	3.5	4.1
Residual							*-0.5*	*-1.5*	*-0.6*	*-0.9*	*0.5*
1983								5.5	5.0	5.1	4.4
Residual								*-0.3*	*0.0*	*0.9*	*1.0*
1984									5.0	3.8	3.2
Residual									*0.2*	*-0.2*	*0.1*
1985										4.9	3.2
Residual										*1.2*	*0.3*
1986											4.0
Residual											*1.3*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 42.15 with 63 degrees of freedom, P = .980.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	8.2
Year (up to 1979, down thereafter)	0.8
Class	−0.2

Table 10

Cocaine: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	6.0	8.9	12.7	18.7	20.1	21.7	23.0	22.4	21.2	21.9	20.0
Residual	*0.7*	*-1.0*	*-1.8*	*-0.4*	*-0.7*	*0.9*	*2.3*	*1.6*	*0.4*	*1.1*	*-0.8*
1977		7.2	10.8	15.8	19.6	20.9	22.6	19.6	21.0	20.8	19.2
Residual		*0.3*	*-0.8*	*-0.3*	*-1.2*	*0.1*	*1.8*	*-1.2*	*0.2*	*0.0*	*-1.6*
1978			9.0	13.3	19.0	18.9	21.3	21.0	20.2	21.6	18.4
Residual			*0.4*	*0.1*	*1.2*	*-1.9*	*0.5*	*0.3*	*-0.6*	*0.9*	*-2.4*
1979				12.0	15.6	18.3	22.4	21.1	21.0	24.1	21.4
Residual				*1.7*	*0.7*	*0.5*	*1.6*	*0.3*	*0.2*	*3.3*	*0.6*
1980					12.3	14.1	19.6	21.6	22.1	22.9	22.5
Residual					*0.4*	*-0.8*	*1.7*	*0.8*	*1.3*	*2.1*	*1.7*
1981						12.4	14.6	17.0	19.3	21.0	22.9
Residual						*0.5*	*-0.3*	*-0.8*	*-1.5*	*0.2*	*2.2*
1982							11.5	11.3	15.7	17.4	20.7
Residual							*-0.4*	*-3.6*	*-2.1*	*-3.4*	*-0.1*
1983								11.4	13.9	18.4	19.8
Residual								*-0.6*	*-1.0*	*0.6*	*-1.0*
1984									11.6	14.1	18.5
Residual									*-0.3*	*-0.8*	*0.6*
1985										13.1	15.6
Residual										*1.2*	*0.7*
1986											12.7
Residual											*0.8*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 39.83 with 63 degrees of freedom, P = .990.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	5.3
Year(up to 1980, constant thereafter)	1.7
Age (up to 21, constant thereafter)	2.9

Table 11

Amphetamine: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	15.8	18.0	19.4	24.2	26.2	26.5	20.6	16.8	14.4	10.6	9.5
Residual	*3.4*	*3.0*	*1.6*	*3.7*	*3.8*	*2.0*	*-0.5*	*-0.8*	*0.1*	*-0.3*	*2.0*
1977		16.3	17.0	21.8	24.5	25.5	22.4	18.1	15.1	12.7	8.2
Residual		*1.2*	*-0.7*	*1.4*	*1.3*	*0.3*	*0.7*	*-0.3*	*0.1*	*1.1*	*0.0*
1978			17.1	21.7	24.8	26.4	21.7	18.3	13.6	12.0	7.6
Residual			*-0.7*	*1.3*	*1.6*	*0.5*	*-0.8*	*-0.8*	*-2.1*	*-0.2*	*-1.3*
1979				18.3	23.3	25.3	23.0	19.8	14.7	13.3	9.0
Residual				*-2.2*	*0.1*	*-0.6*	*-0.2*	*0.0*	*-1.6*	*0.4*	*-0.6*
1980					20.8	25.2	23.8	19.4	17.2	14.2	10.0
Residual					*-2.4*	*-0.7*	*0.6*	*-1.0*	*0.1*	*0.5*	*-0.3*
1981						26.0	21.9	20.1	16.5	12.6	11.5
Residual						*0.1*	*-1.2*	*-0.4*	*-1.3*	*-1.8*	*0.5*
1982							22.9	18.3	15.1	12.6	11.7
Residual							*-0.2*	*-2.2*	*-2.6*	*-2.5*	*0.0*
1983								24.6	17.5	14.3	14.3
Residual								*4.2*	*-0.3*	*-0.7*	*1.9*
1984									17.7	14.7	11.9
Residual									*-0.1*	*-0.3*	*-0.5*
1985										15.8	10.8
Residual										*0.7*	*-1.5*
1986											13.4
Residual											*1.0*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 50.13 with 63 degrees of freedom, P = .880.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	12.4
Year (up to 1981, down thereafter)	2.7
Age(constant to 21, down thereafter)	−0.7

Table 12

Methaqualone: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	4.7	5.1	5.0	7.3	8.5	8.7	6.7	4.7	2.8	1.3	1.2
Residual	*0.0*	*0.0*	*-0.1*	*0.9*	*0.8*	*1.0*	*0.3*	*-0.3*	*-0.9*	*-1.0*	*0.3*
1977		5.2	5.4	6.2	7.8	8.9	8.9	5.1	3.7	1.5	1.0
Residual		*0.0*	*0.3*	*-0.2*	*0.0*	*1.2*	*2.5*	*0.1*	*0.1*	*-0.8*	*0.0*
1978			4.9	6.2	7.4	11.2	6.3	4.9	3.4	1.7	1.2
Residual			*-0.2*	*-0.2*	*-0.3*	*3.5*	*-0.1*	*-0.1*	*-0.2*	*-0.6*	*0.3*
1979				5.9	7.8	8.5	7.5	5.0	2.8	1.7	1.1
Residual				*-0.5*	*0.1*	*0.8*	*1.2*	*0.0*	*-0.8*	*-0.6*	*0.2*
1980					7.2	7.2	8.5	4.9	3.6	2.6	1.2
Residual					*-0.5*	*-0.5*	*2.1*	*-0.1*	*0.0*	*0.3*	*0.3*
1981						7.6	6.5	4.2	3.2	2.0	1.3
Residual						*-0.1*	*0.1*	*-0.9*	*-0.4*	*-0.3*	*0.4*
1982							6.8	4.2	2.8	1.7	1.0
Residual							*0.4*	*-0.8*	*-0.8*	*-0.6*	*0.1*
1983								5.4	3.3	1.4	1.2
Residual								*0.4*	*-0.3*	*-0.8*	*0.3*
1984									3.8	2.1	1.8
Residual									*0.1*	*-0.2*	*0.9*
1985										2.8	1.4
Residual										*0.5*	*0.4*
1986											2.1
Residual											*1.2*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 44.60 with 59 degrees of freedom, P = .918.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	9.1
Year (unconstrained, 1976–1980, down thereafter)	−1.4

Table 13

Barbiturate: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	9.6	7.6	5.2	7.4	5.0	5.6	4.2	3.1	3.1	1.8	1.6
Residual	*0.3*	*0.8*	*-1.1*	*1.7*	*-0.2*	*0.9*	*0.0*	*-0.5*	*0.1*	*-0.7*	*-0.3*
1977		9.3	6.4	7.2	5.3	6.2	3.9	3.5	3.0	3.4	2.6
Residual		*0.5*	*0.1*	*1.5*	*0.1*	*1.5*	*-0.2*	*0.0*	*0.0*	*0.9*	*0.7*
1978			8.1	5.3	5.4	4.9	4.4	3.5	3.3	3.3	2.0
Residual			*-0.1*	*-0.4*	*0.2*	*0.2*	*0.3*	*-0.1*	*0.2*	*0.9*	*0.0*
1979				7.5	5.7	5.1	3.8	3.5	2.0	2.9	1.8
Residual				*-0.2*	*0.4*	*0.4*	*-0.3*	*0.0*	*-1.0*	*0.4*	*-0.1*
1980					6.8	4.3	4.6	2.6	3.0	3.1	1.7
Residual					*-0.3*	*-0.4*	*0.5*	*-1.0*	*0.0*	*0.6*	*-0.2*
1981						6.6	3.7	4.8	1.9	2.1	2.8
Residual						*0.0*	*-0.4*	*1.2*	*-1.1*	*-0.4*	*0.9*
1982							5.5	2.3	3.2	2.6	2.5
Residual							*-0.5*	*-1.2*	*0.2*	*0.1*	*0.6*
1983								5.2	3.6	2.3	3.2
Residual								*-0.3*	*0.6*	*-0.2*	*1.2*
1984									4.9	1.7	2.5
Residual									*0.0*	*-0.8*	*0.5*
1985										4.6	1.9
Residual										*0.2*	*0.0*
1986											4.2
Residual											*0.4*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 37.76 with 63 degrees of freedom, P = .995.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	9.3
Year	−0.6
Age (18 ≠ 19-24)	−1.9

Table 14

LSD: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976 .	6.4	6.7	6.9	8.3	7.8	6.8	5.8	5.4	2.3	2.4	2.0
Residual	*0.0*	*-0.1*	*-0.2*	*0.8*	*1.2*	*1.0*	*1.0*	*1.5*	*-0.8*	*0.2*	*0.7*
1977 .		5.5	6.1	8.2	8.3	7.4	6.0	4.0	3.0	2.6	1.2
Residual		*-1.5*	*-1.4*	*0.4*	*1.3*	*1.4*	*0.8*	*-0.2*	*-0.3*	*0.2*	*-0.4*
1978 .			6.3	7.7	7.3	8.3	6.1	4.9	3.4	3.1	0.9
Residual			*-1.4*	*-0.3*	*0.2*	*2.0*	*0.7*	*0.5*	*-0.2*	*0.5*	*-0.9*
1979 .				6.6	6.8	6.6	7.2	4.4	2.7	2.2	1.9
Residual				*-1.7*	*-0.6*	*0.1*	*1.6*	*-0.3*	*-1.1*	*-0.8*	*-0.1*
1980 .					6.5	6.5	7.7	5.4	4.7	3.6	2.1
Residual					*-1.2*	*-0.3*	*1.9*	*0.4*	*0.6*	*0.4*	*-0.1*
1981 .						6.5	7.0	5.6	5.5	2.6	3.1
Residual						*-0.5*	*0.9*	*0.4*	*1.2*	*-0.8*	*0.6*
1982 .							6.1	5.0	4.4	3.9	5.0
Residual							*-0.2*	*-0.5*	*-0.1*	*0.2*	*2.2*
1983 .								5.4	3.8	3.5	3.3
Residual								*-0.3*	*-1.0*	*-0.4*	*0.3*
1984 .									4.7	3.8	5.4
Residual									*-0.4*	*-0.3*	*2.2*
1985 .										4.4	4.1
Residual										*0.0*	*0.6*
1986 .											4.5
Residual											*0.7*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 56.96 with 63 degrees of freedom, P = .690

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	6.4
Year (up to 1979, down thereafter)	0.7
Age	−0.2

Table 15

Psychedelics: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	7.0	6.9	7.2	7.2	6.0	4.1	3.0	4.6	2.3	2.6	1.4
Residual	*-1.2*	*-0.7*	*0.2*	*0.7*	*0.2*	*-1.1*	*-1.6*	*0.6*	*-1.1*	*-0.2*	*-0.8*
1977		6.9	7.1	8.0	5.2	6.8	4.5	4.0	3.4	2.3	1.0
Residual		*-0.7*	*0.1*	*1.6*	*-0.6*	*1.6*	*-0.1*	*0.0*	*0.0*	*-0.5*	*-1.2*
1978			7.3	6.8	6.0	5.9	5.5	4.3	3.6	2.8	2.0
Residual			*0.3*	*0.4*	*0.1*	*0.7*	*0.9*	*0.3*	*0.3*	*0.1*	*-0.2*
1979				6.8	5.7	4.8	4.7	3.3	3.4	2.4	2.0
Residual				*0.4*	*-0.2*	*-0.4*	*0.1*	*-0.7*	*0.0*	*-0.4*	*-0.1*
1980					6.2	4.7	5.9	5.4	4.1	3.3	2.0
Residual					*0.4*	*-0.5*	*1.3*	*1.4*	*0.7*	*0.5*	*-0.2*
1981						5.6	5.5	4.8	3.8	4.5	2.8
Residual						*0.4*	*0.9*	*0.8*	*0.4*	*1.7*	*0.7*
1982							4.7	2.8	3.7	2.8	2.8
Residual							*0.1*	*-1.2*	*0.3*	*0.0*	*0.7*
1983								4.1	2.5	3.3	1.9
Residual								*0.1*	*-0.9*	*0.5*	*-0.2*
1984									3.8	3.1	3.8
Residual									*0.5*	*0.3*	*1.7*
1985										3.6	3.5
Residual										*0.8*	*1.3*
1986											3.0
Residual											*0.8*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 53.99 with 64 degrees of freedom, P = .810.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	8.2
Year	−0.6

Table 16

Tranquilizer: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	10.3	10.4	8.2	10.1	8.8	10.6	9.5	8.6	5.9	5.4	6.2
Residual	*-0.4*	*0.3*	*-1.3*	*1.2*	*0.4*	*2.9*	*2.3*	*2.1*	*-0.1*	*0.1*	*1.4*
1977		10.8	9.7	10.0	7.5	8.2	7.3	7.1	6.9	7.1	6.4
Residual		*0.7*	*0.1*	*1.0*	*-0.8*	*0.5*	*0.2*	*0.5*	*1.0*	*1.7*	*1.6*
1978			9.9	10.0	10.3	6.2	6.3	6.1	6.6	7.2	4.9
Residual			*0.4*	*1.1*	*2.0*	*-1.5*	*-0.8*	*-0.4*	*0.6*	*1.9*	*0.1*
1979				9.6	8.2	7.9	7.7	6.4	4.8	7.2	5.8
Residual				*0.7*	*-0.2*	*0.2*	*0.6*	*-0.2*	*-1.1*	*1.8*	*1.0*
1980					8.7	7.3	5.3	5.4	5.8	5.6	5.7
Residual					*0.4*	*-0.4*	*-1.8*	*-1.2*	*-0.1*	*0.2*	*0.9*
1981						8.0	5.9	5.0	5.1	5.0	4.5
Residual						*0.3*	*-1.3*	*-1.6*	*-0.9*	*-0.4*	*-0.2*
1982							7.0	4.9	5.4	4.0	4.7
Residual							*-0.1*	*-1.7*	*-0.6*	*-1.3*	*-0.1*
1983								6.9	5.1	4.8	5.5
Residual								*0.4*	*-0.9*	*-0.6*	*0.7*
1984									6.1	3.9	5.2
Residual									*0.2*	*-1.5*	*0.4*
1985										6.1	3.1
Residual										*0.7*	*-1.6*
1986											5.8
Residual											*1.0*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 62.04 with 64 degrees of freedom, P = .546.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	10.7
Year	−0.6

Table 17

Heroin: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	0.8	0.5	0.4	0.8	0.7	0.5	0.2	0.4	0.3	0.3	0.3
Residual	*0.6*	*0.4*	*0.2*	*0.6*	*0.5*	*0.3*	*0.0*	*0.2*	*0.1*	*0.1*	*0.1*
1977		0.8	0.3	0.3	0.6	0.2	0.2	0.7	0.2	0.5	0.3
Residual		*0.6*	*0.1*	*0.1*	*0.5*	*0.0*	*0.0*	*0.5*	*0.0*	*0.3*	*0.1*
1978			0.8	0.2	0.3	0.4	0.3	0.4	0.2	0.2	0.2
Residual			*0.6*	*0.0*	*0.1*	*0.2*	*0.1*	*0.2*	*0.0*	*0.0*	*0.1*
1979				0.5	0.1	0.7	0.4	0.1	0.1	0.4	0.1
Residual				*0.3*	*-0.1*	*0.5*	*0.3*	*0.0*	*0.0*	*0.2*	*-0.1*
1980					0.5	0.3	0.2	0.4	0.3	0.1	0.2
Residual					*0.3*	*0.1*	*0.0*	*0.2*	*0.1*	*-0.1*	*0.0*
1981						0.5	0.2	0.3	0.2	0.5	0.1
Residual						*0.3*	*0.0*	*0.1*	*0.0*	*0.3*	*-0.1*
1982							0.6	0.1	0.2	0.0	0.3
Residual							*0.4*	*-0.1*	*0.0*	*-0.2*	*0.1*
1983								0.6	0.1	0.1	0.1
Residual								*0.4*	*-0.1*	*-0.1*	*-0.1*
1984									0.5	0.1	0.0
Residual									*0.3*	*-0.1*	*-0.2*
1985										0.6	0.1
Residual										*0.4*	*-0.1*
1986											0.5
Residual											*0.3*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 50.79 with 65 degrees of freedom, P = .902.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	0.2

Table 18

Narcotics: Annual Prevalence

Class Year	Year of Data Collection										
	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
1976	5.7	4.9	4.3	5.9	4.9	3.6	3.7	3.5	2.3	2.9	2.3
Residual	*0.7*	*0.2*	*-0.1*	*1.8*	*1.1*	*0.1*	*0.5*	*0.7*	*-0.3*	*0.6*	*0.3*
1977		6.4	5.4	5.0	5.5	4.9	4.9	3.5	2.9	4.5	2.7
Residual		*1.4*	*0.7*	*0.6*	*1.4*	*1.1*	*1.4*	*0.3*	*0.1*	*1.9*	*0.4*
1978			6.0	4.0	5.9	4.8	2.7	2.8	3.8	2.2	1.7
Residual			*1.0*	*-0.6*	*1.5*	*0.7*	*-1.1*	*-0.7*	*0.6*	*-0.7*	*-0.9*
1979				6.2	4.5	4.8	3.7	4.1	3.0	3.9	2.2
Residual				*1.2*	*-0.2*	*0.4*	*-0.4*	*0.4*	*-0.5*	*0.7*	*-0.7*
1980					6.3	4.8	5.4	3.7	3.1	3.6	2.9
Residual					*1.3*	*0.1*	*1.0*	*-0.4*	*-0.6*	*0.1*	*-0.3*
1981						5.9	3.5	4.4	3.4	4.1	2.5
Residual						*0.9*	*-1.2*	*0.0*	*-0.7*	*0.3*	*-1.0*
1982							5.3	4.0	3.6	3.5	3.5
Residual							*0.3*	*-0.7*	*-0.8*	*-0.6*	*-0.3*
1983								5.1	3.6	4.1	3.8
Residual								*0.1*	*-1.0*	*-0.3*	*-0.3*
1984									5.2	2.7	3.8
Residual									*0.2*	*-1.9*	*-0.6*
1985										5.9	4.3
Residual										*0.9*	*-0.3*
1986											5.2
Residual											*0.2*

Notes:

In each cell, the first entry is the observed prevalence; the second entry is the residual (the observed value minus the value predicted by the model summarized below). (All calculations used more places of accuracy than shown.)

Chi-square = 57.01 with 64 degrees of freedom, P = .720.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	5.0
Age	−0.3

Figure 1

Cigarettes: Monthly Prevalence

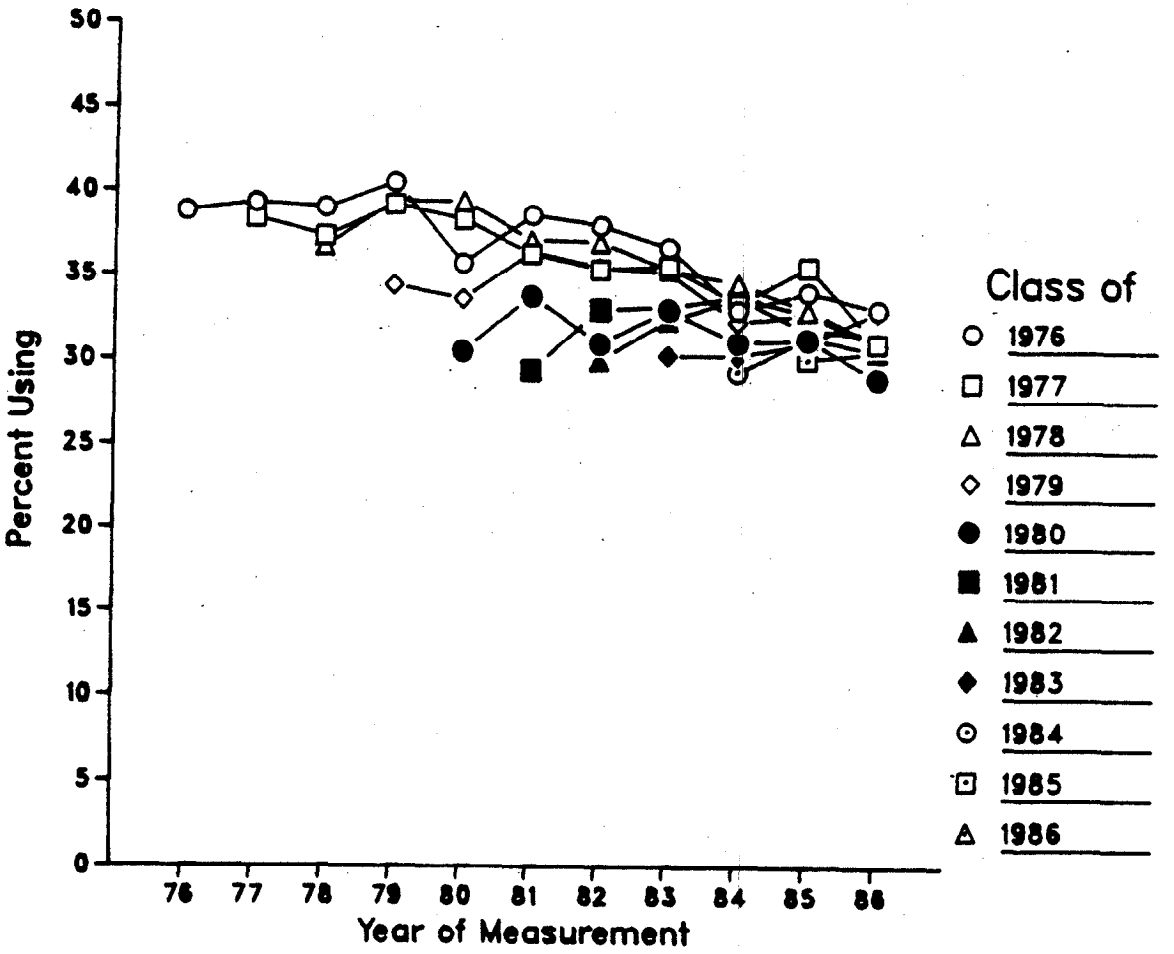

Figure 2

Cigarettes: Daily Prevalence (Any)

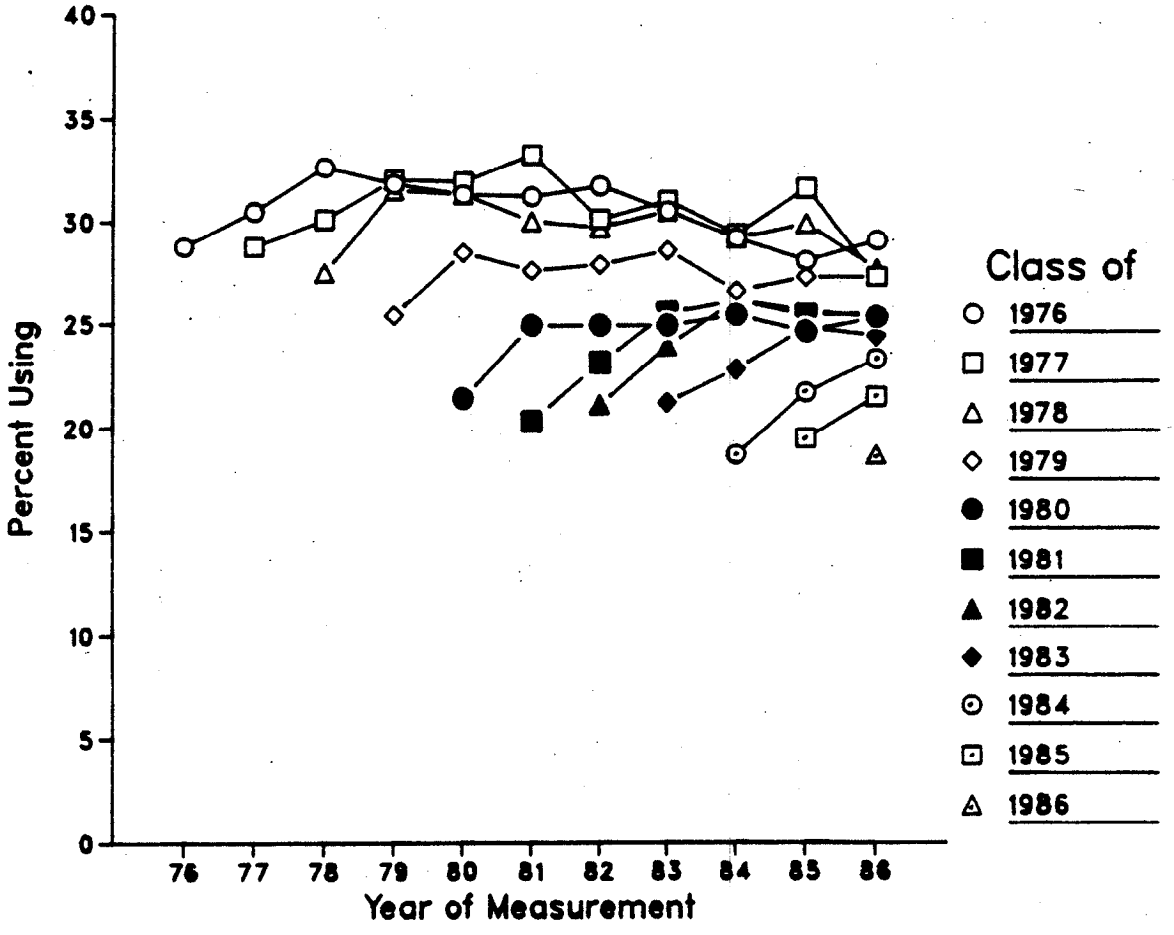

Figure 3

Cigarettes: Daily Prevalence (1/2 Pack Per Day)

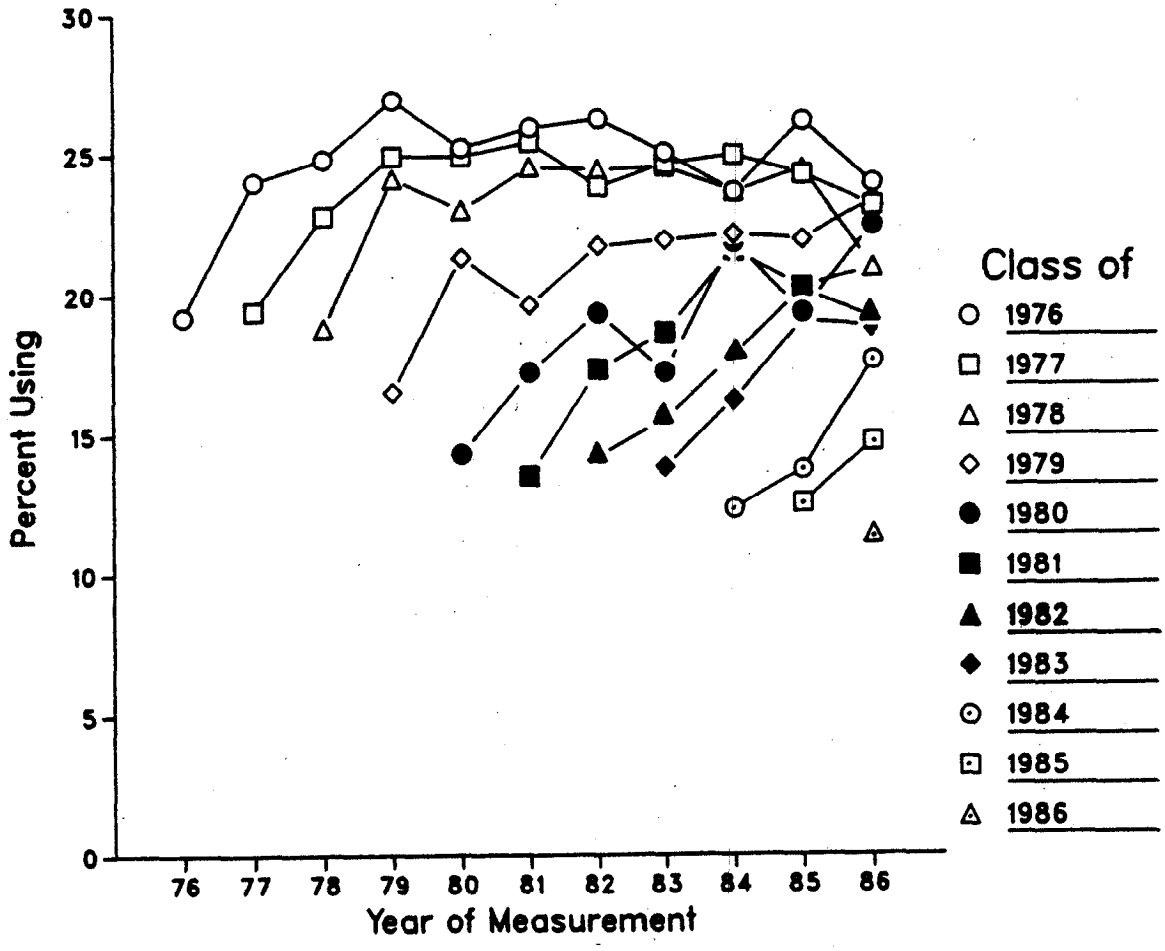

Figure 4

Alcohol: Monthly Prevalence

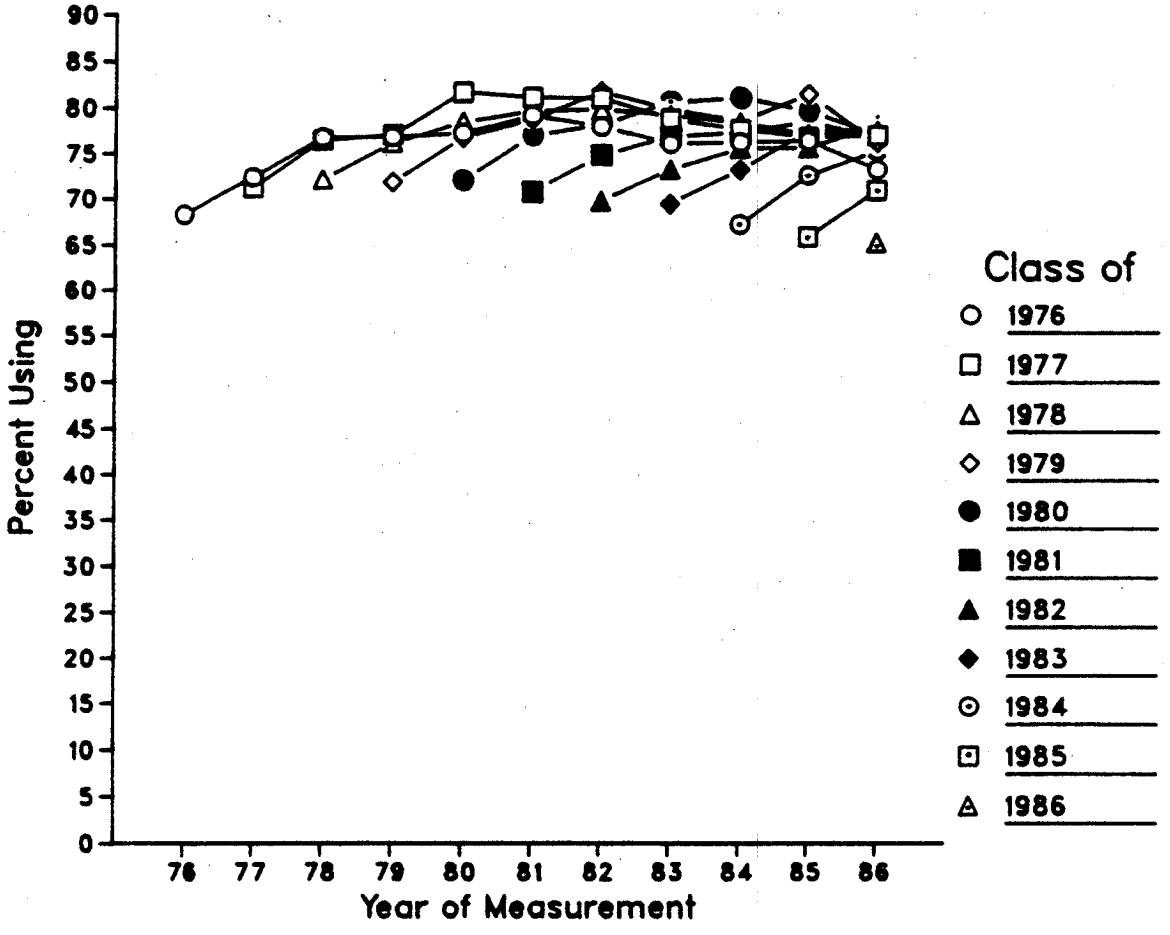

Figure 5

Alcohol: Daily Prevalence

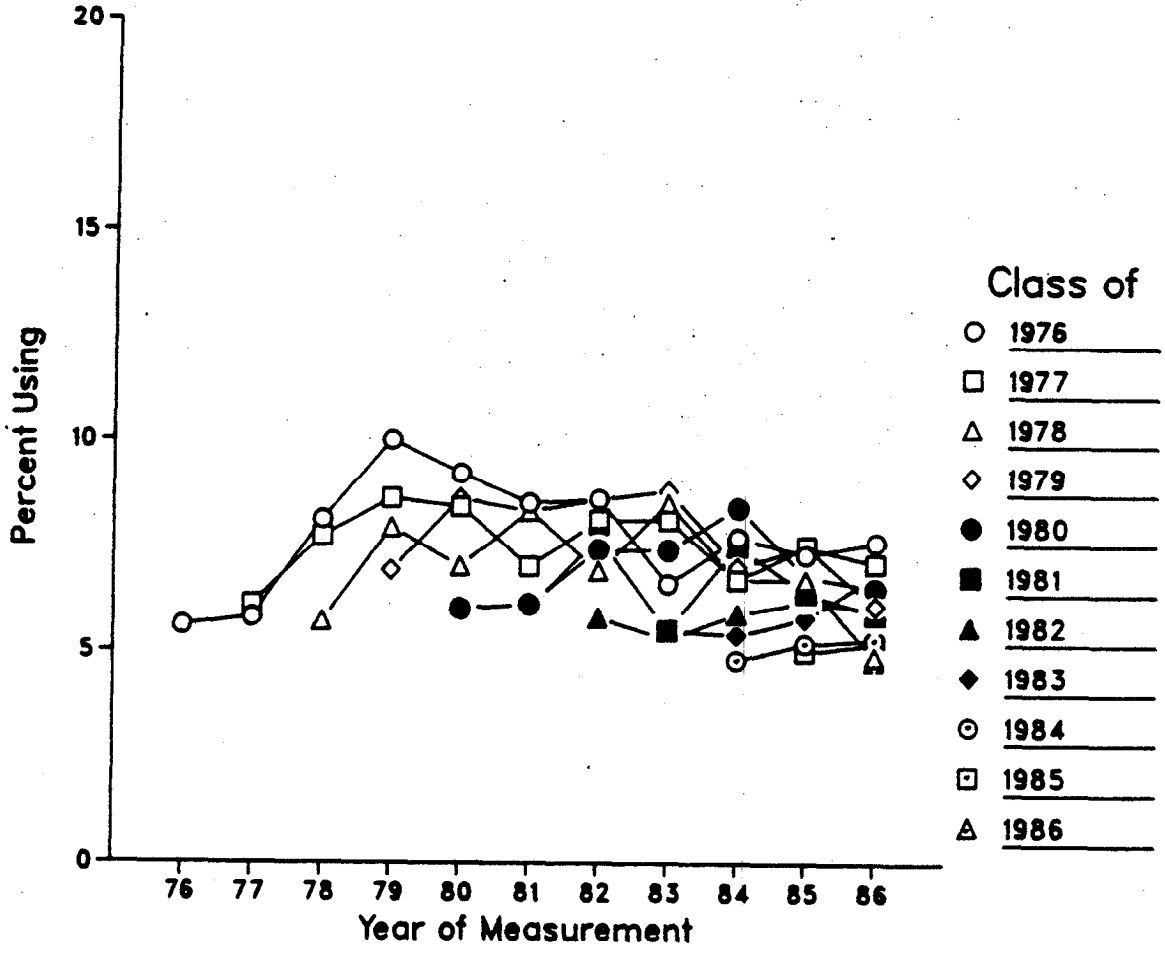

Figure 6

Alcohol: Two Weeks Prevalence (5+ Drinks)

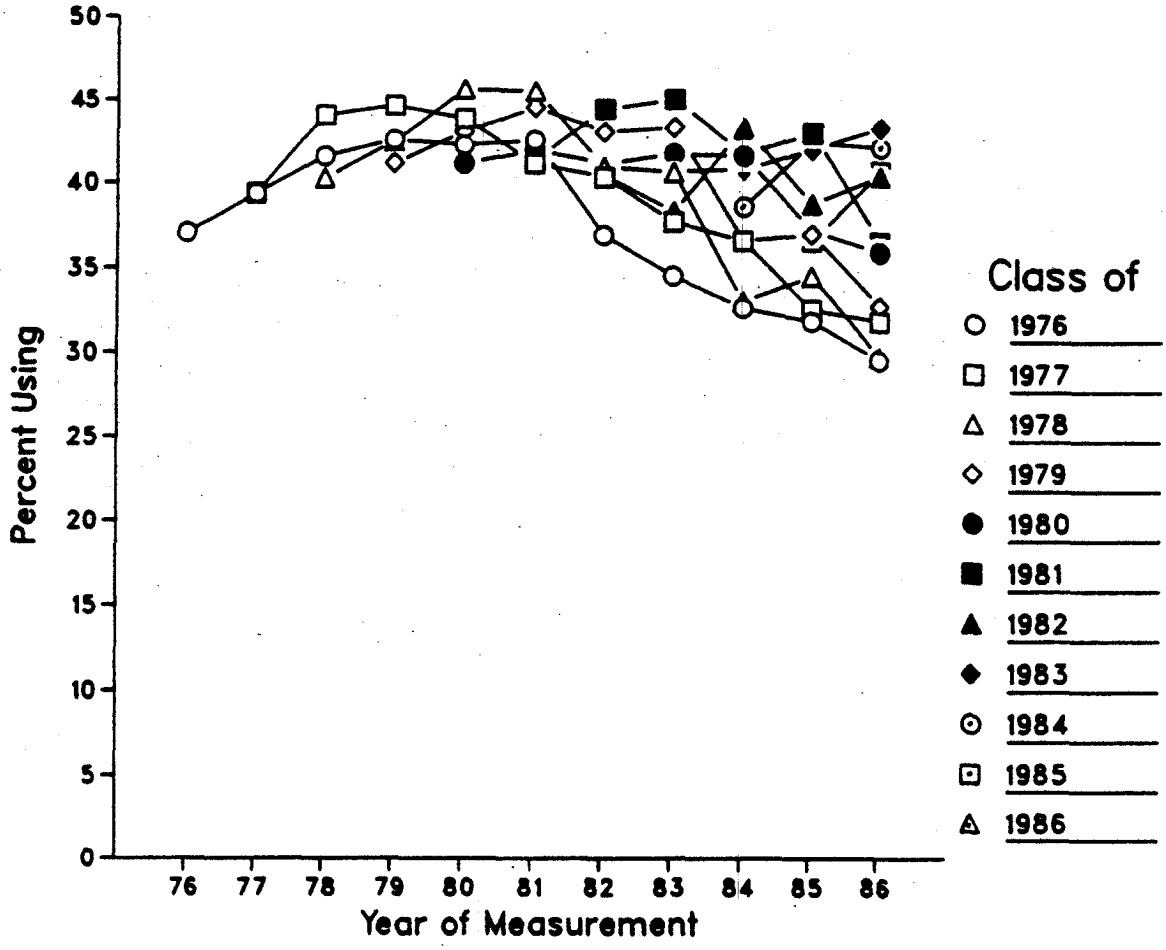

Figure 7

Marijuana: Annual Prevalence

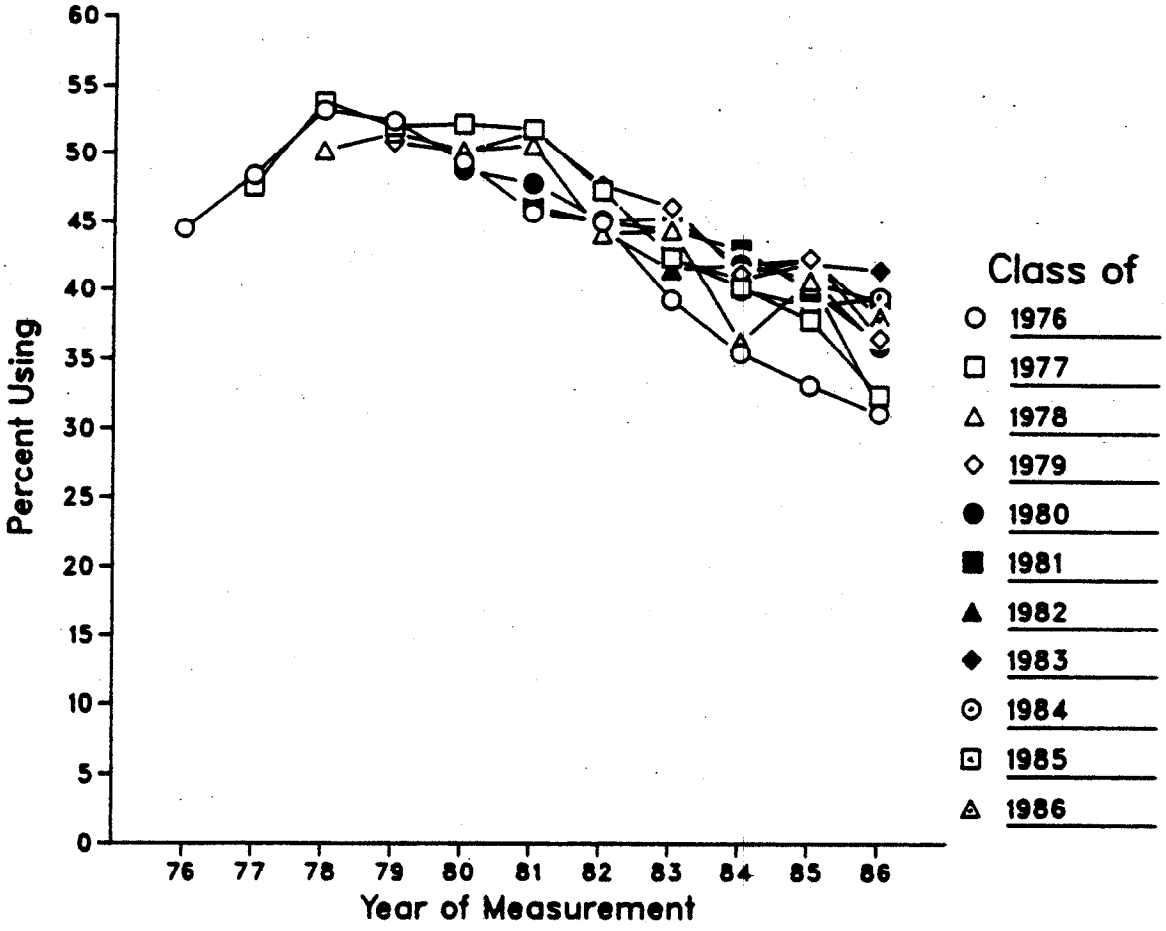

Figure 8

Marijuana: Monthly Prevalence

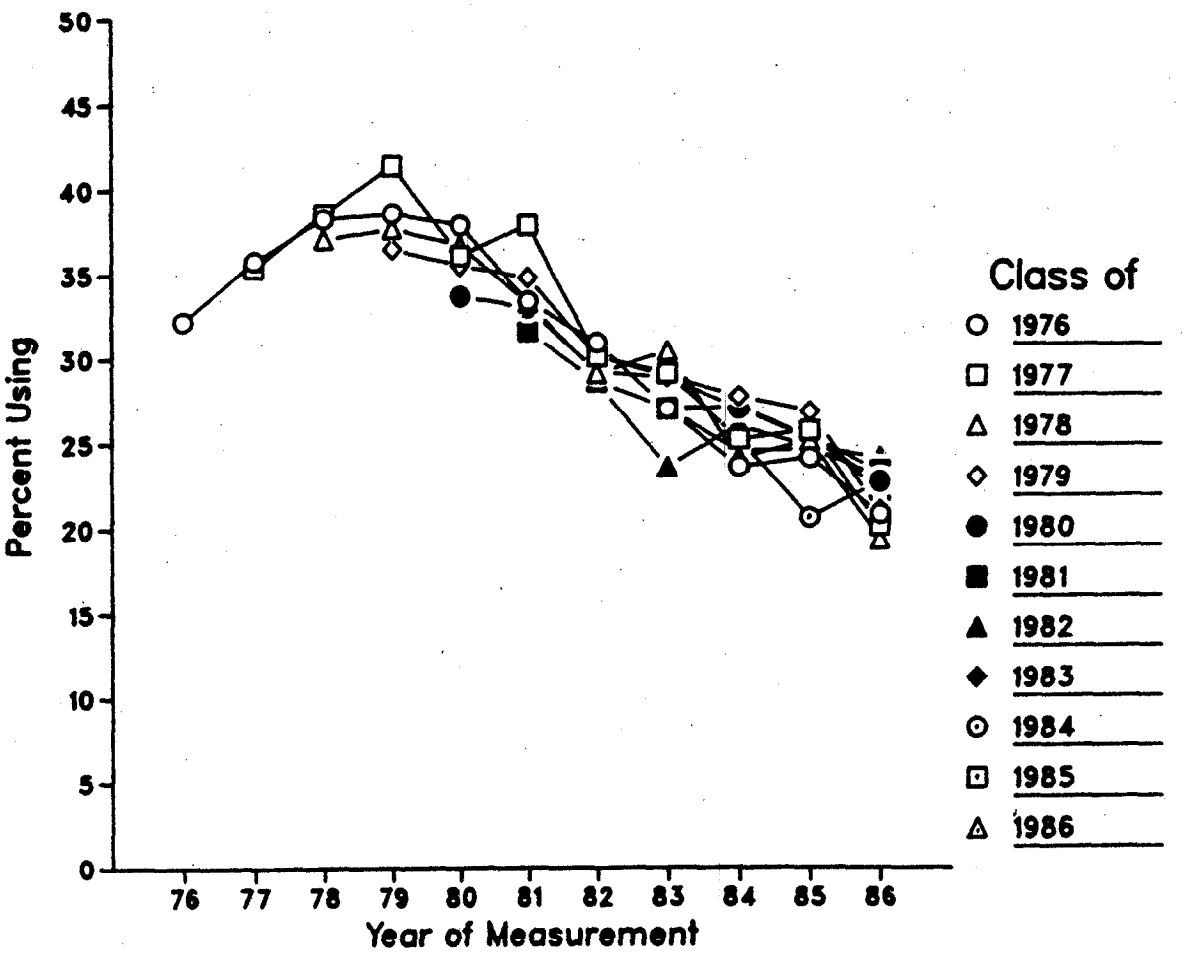

Figure 9

Marijuana: Daily Prevalence

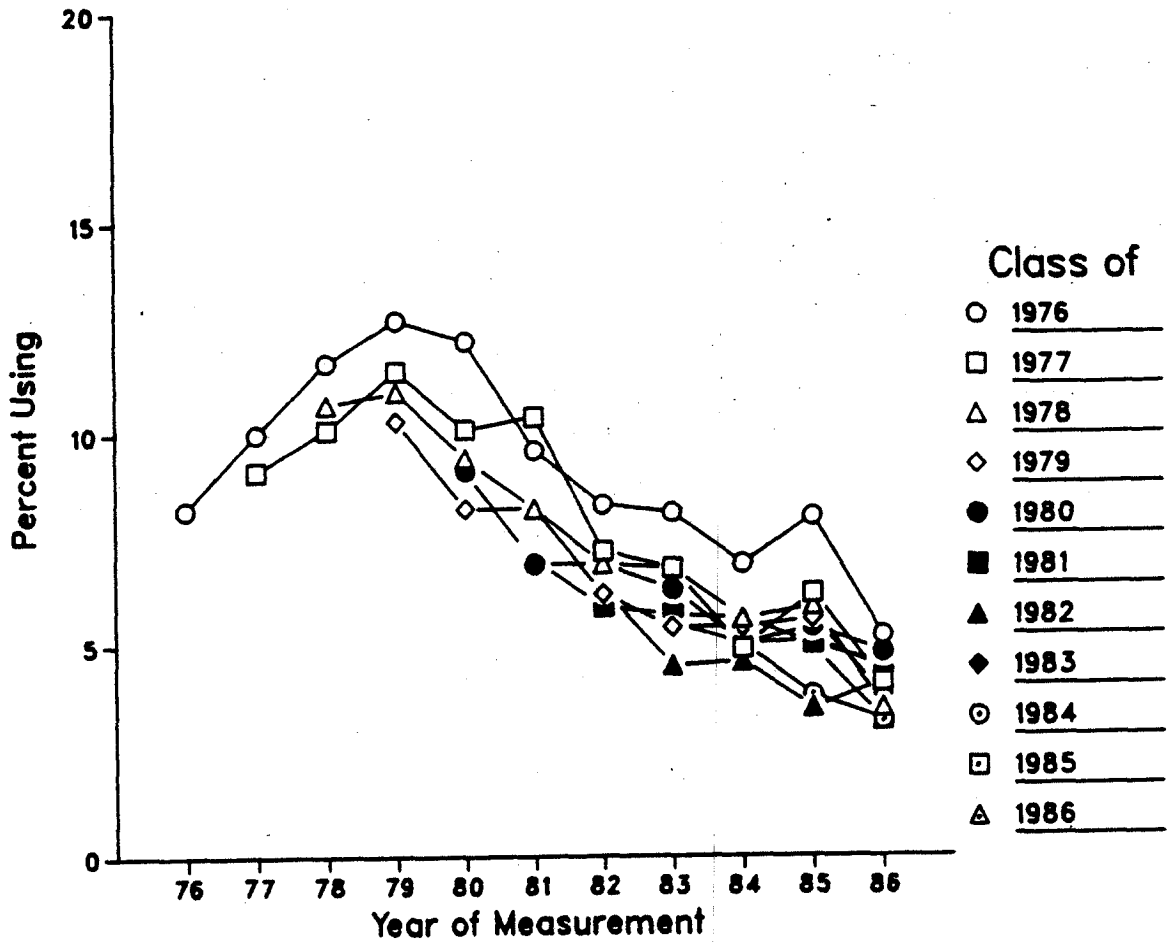

Figure 10

Cocaine: Annual Prevalence

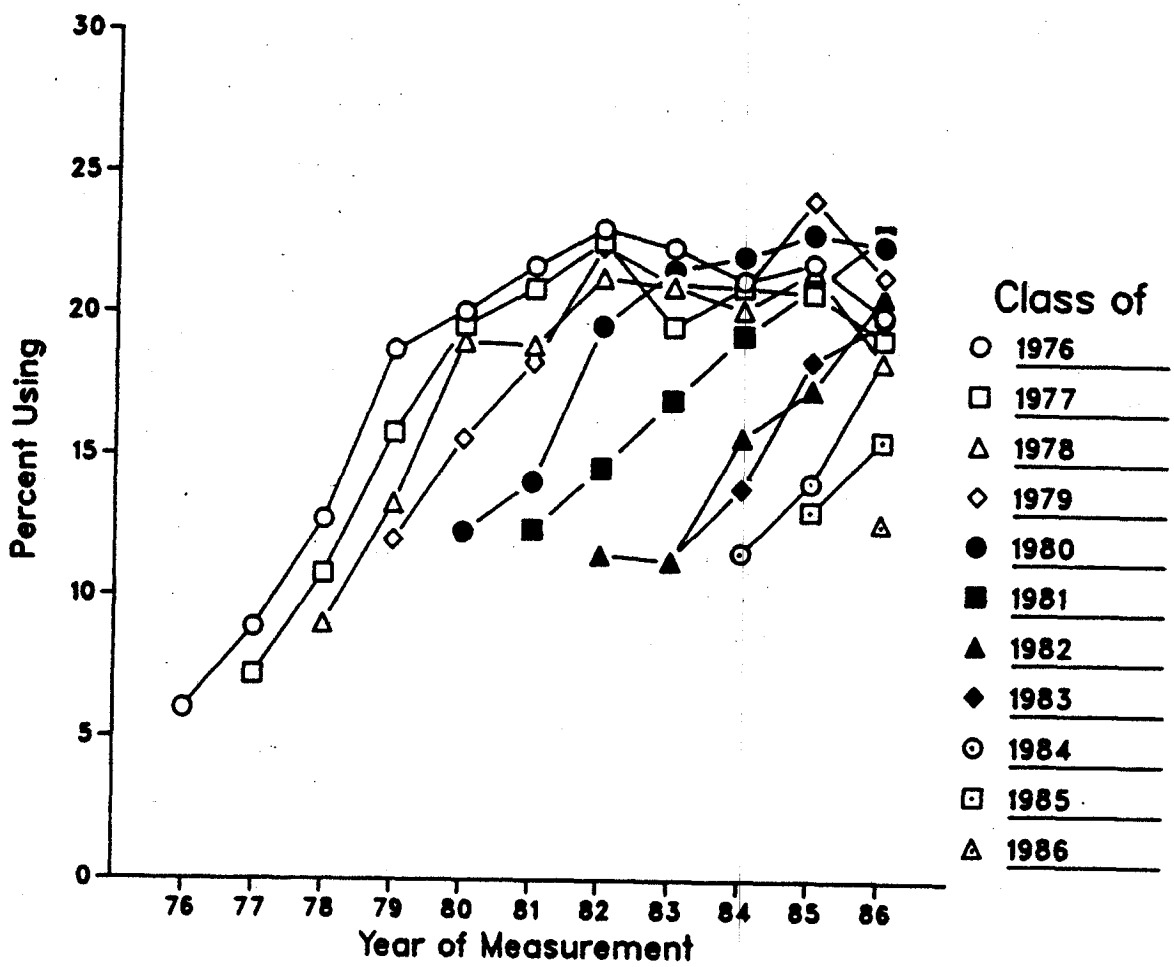

Figure 11

Amphetamine: Annual Prevalence

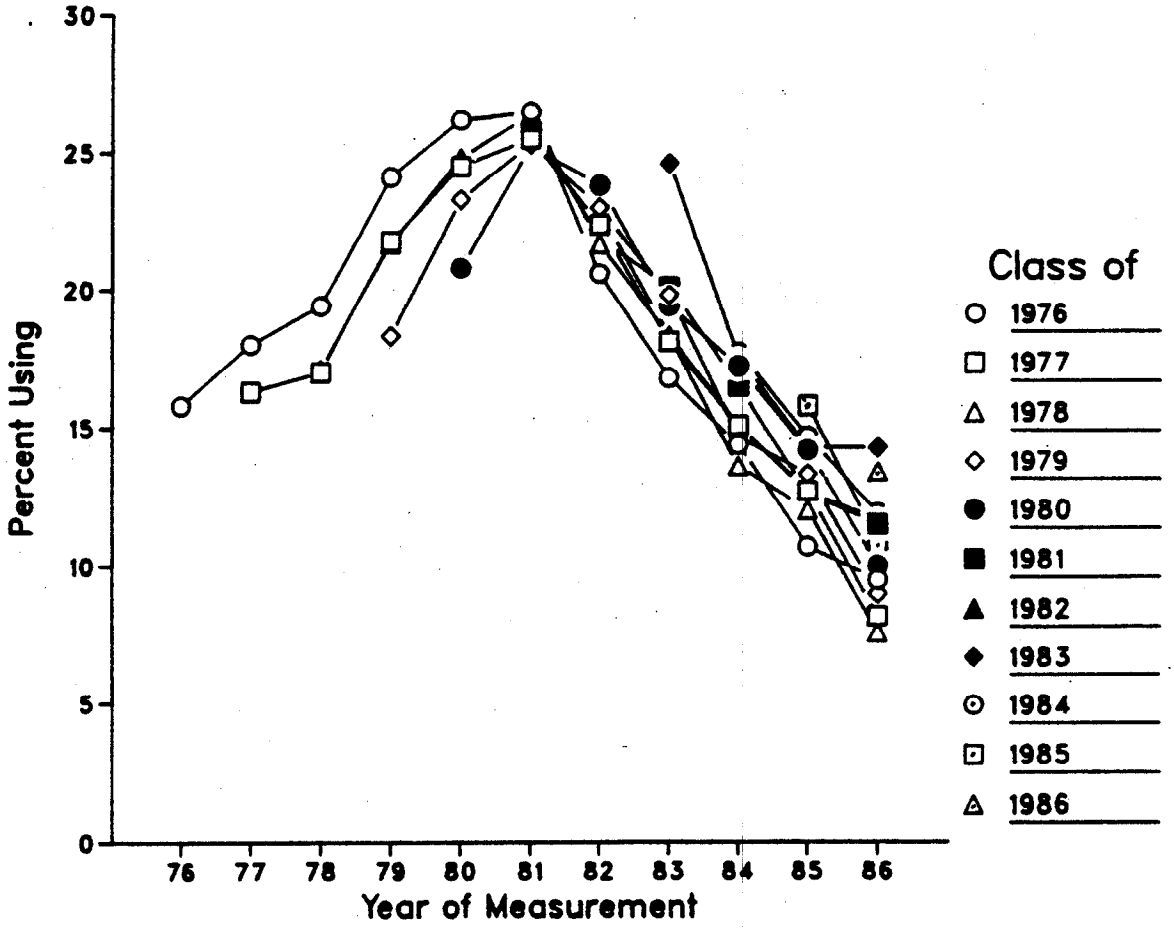

Figure 12

Methaqualone: Annual Prevalence

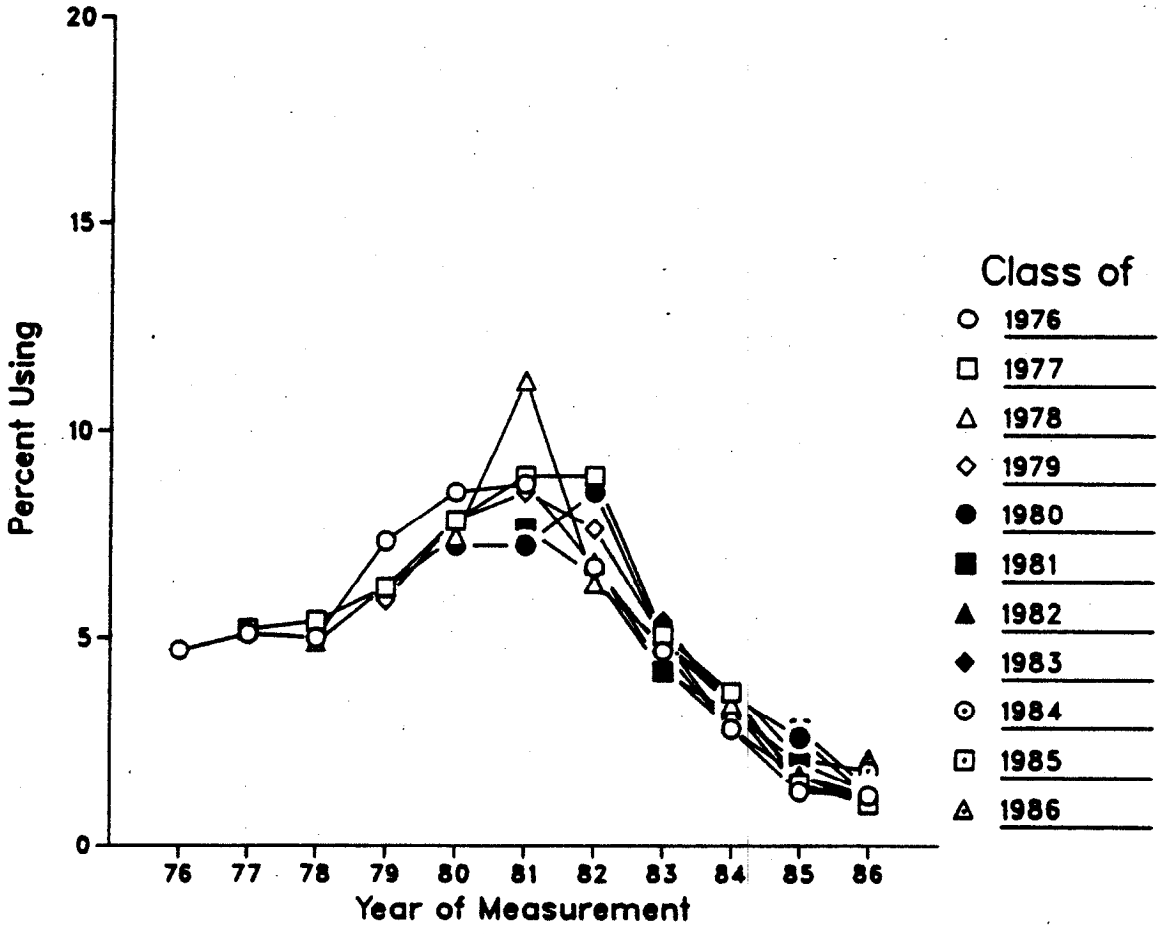

Figure 13

Barbiturate: Annual Prevalence

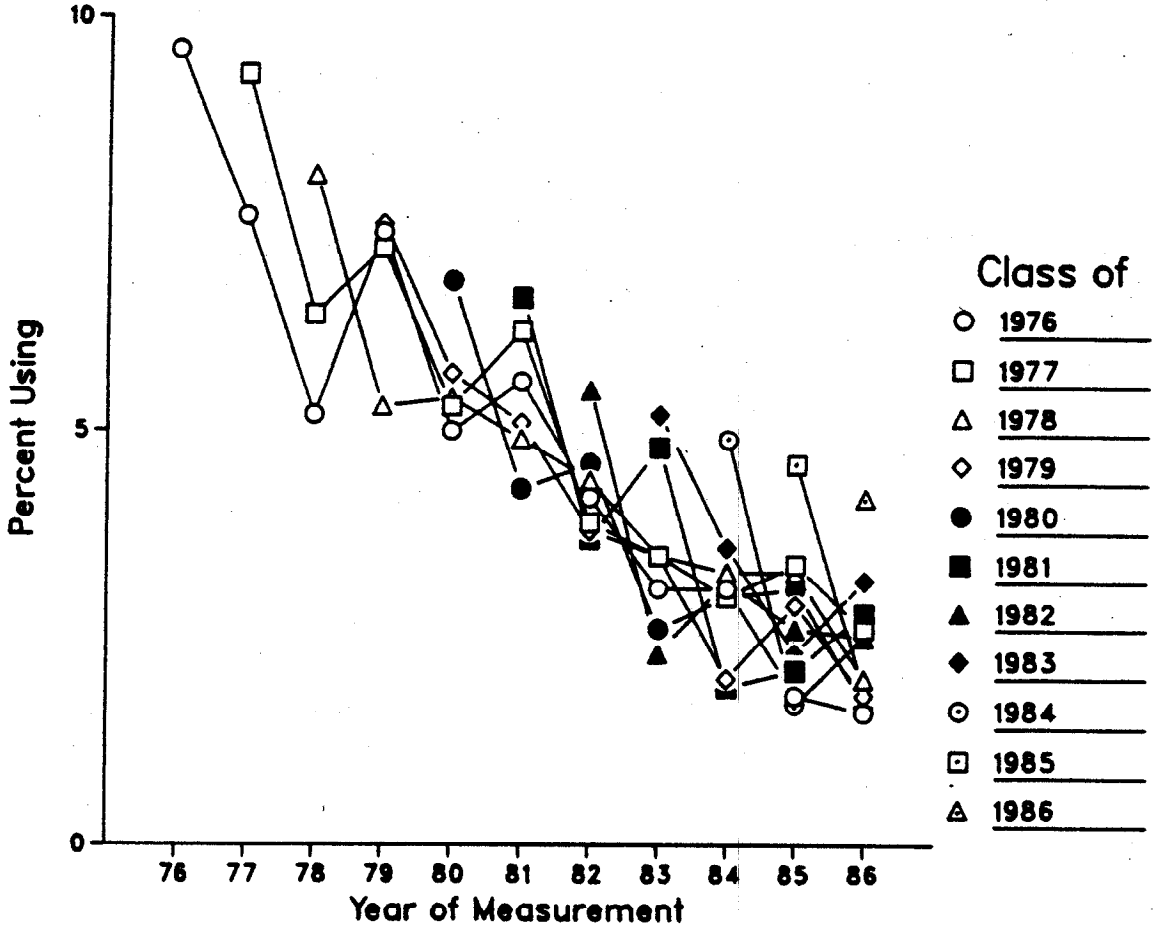

Figure 14

LSD: Annual Prevalence

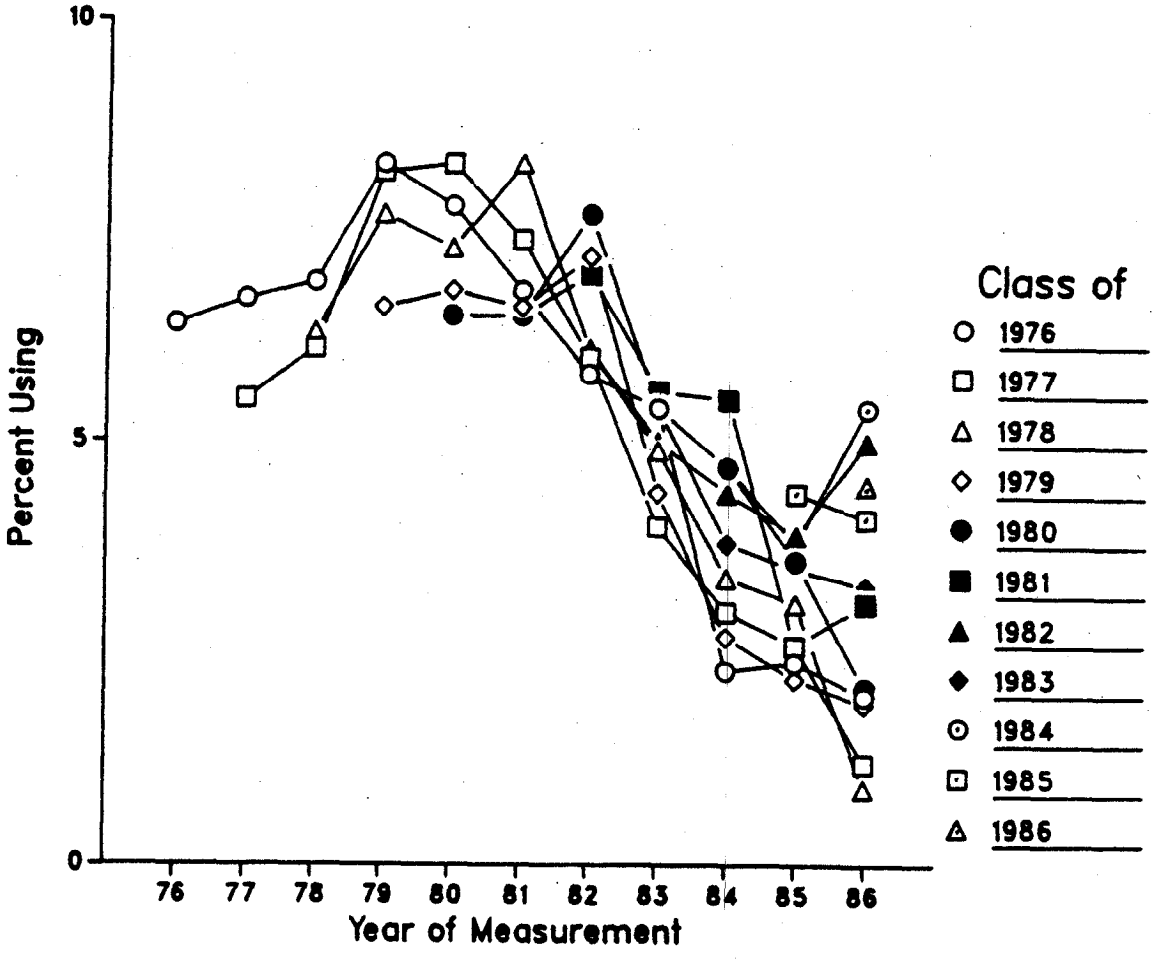

Figure 15

Psychedelics: Annual Prevalence

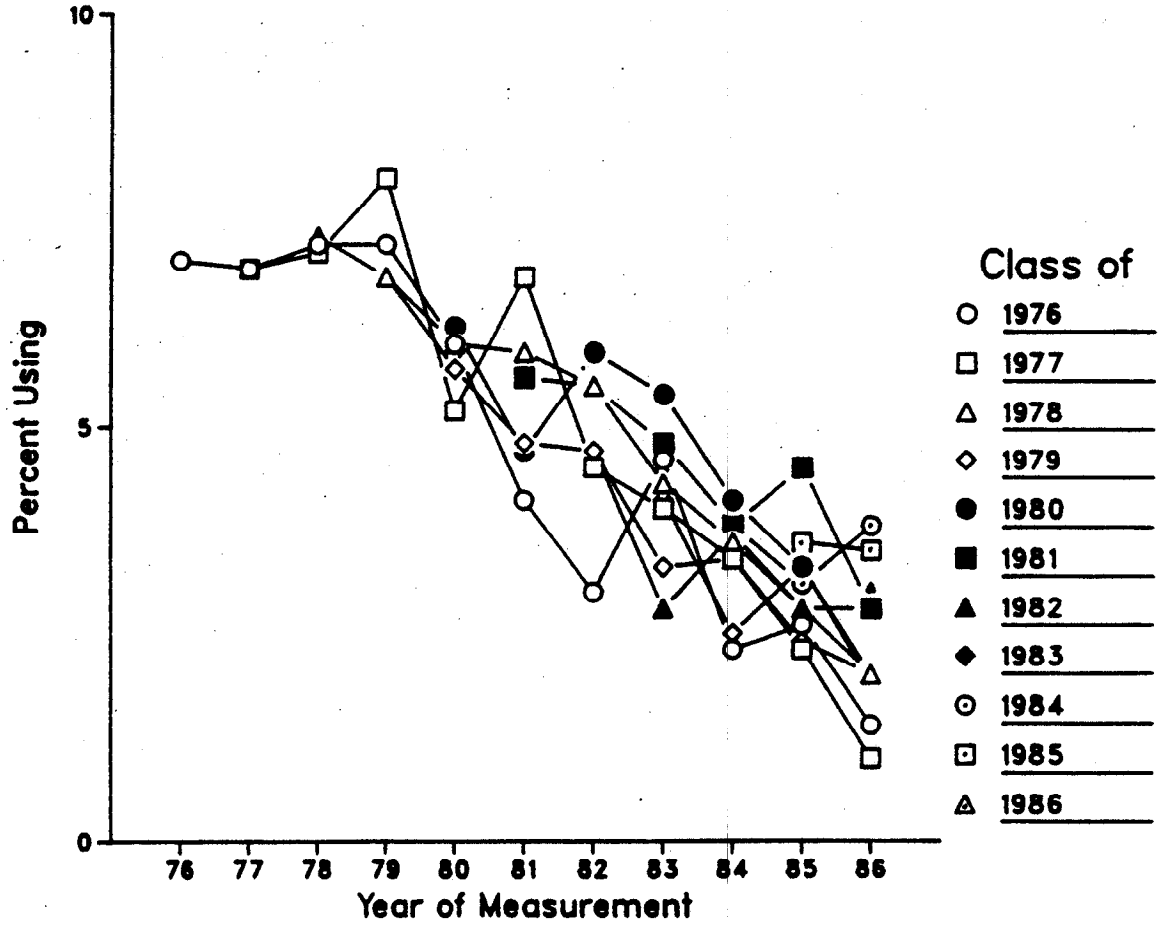

Figure 16

Tranquilizer: Annual Prevalence

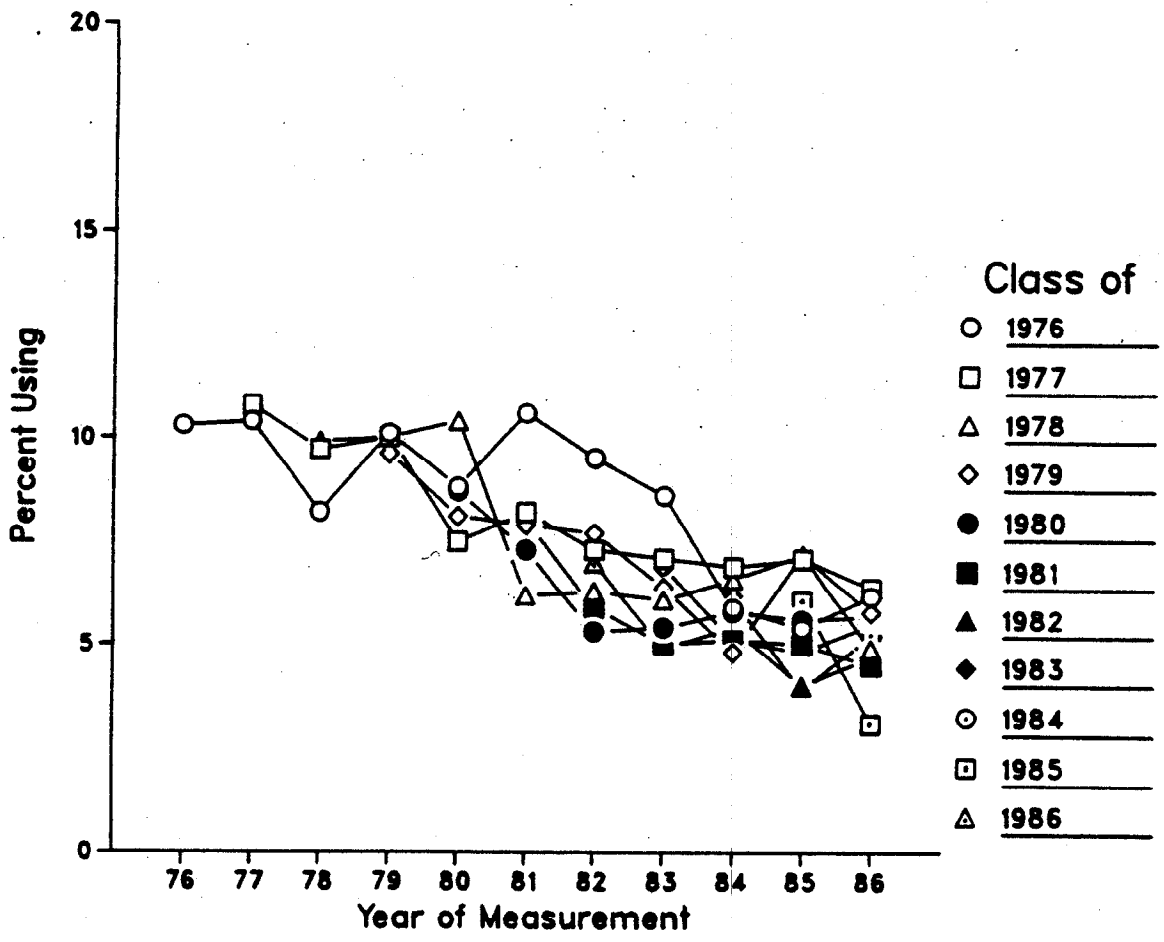

Figure 17

Heroin: Annual Prevalence

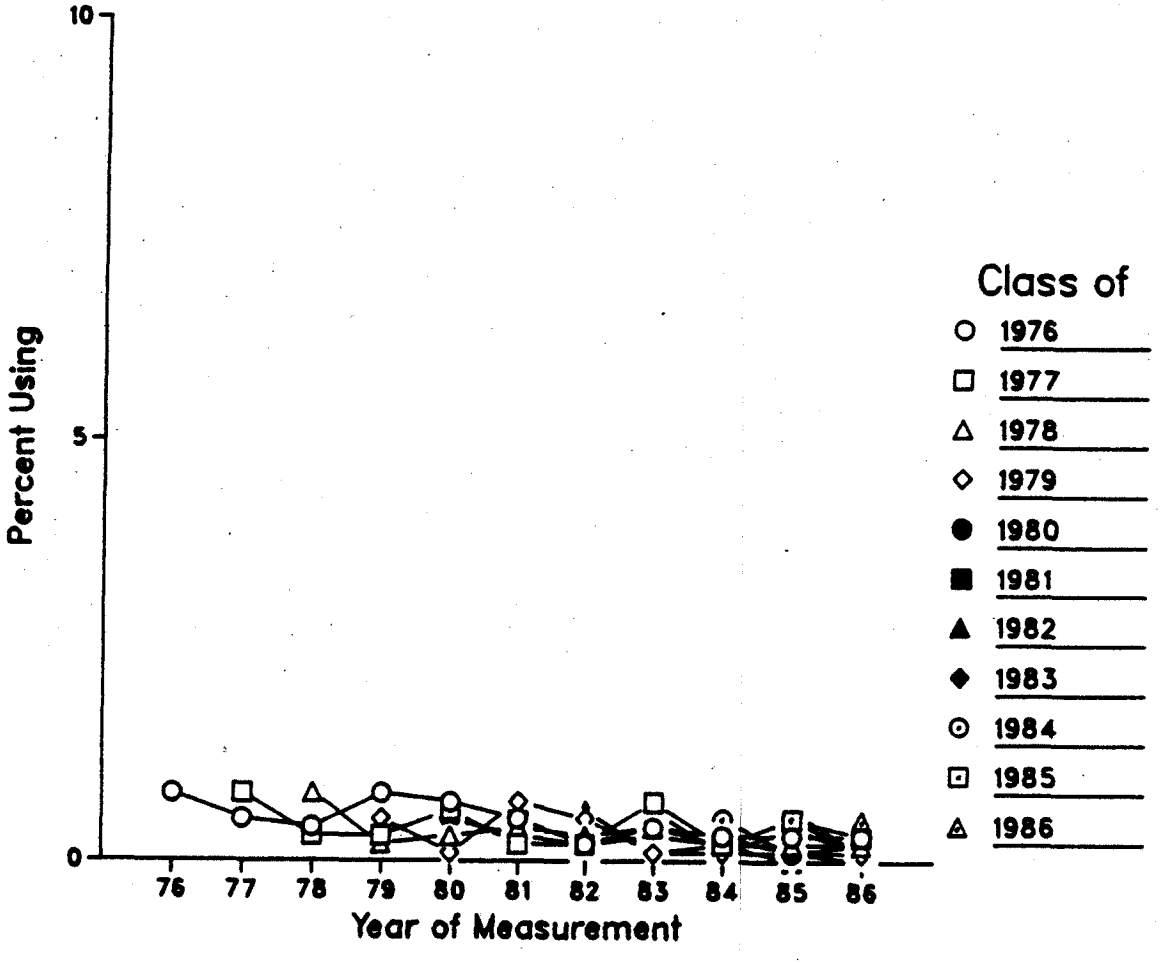

Figure 18

Narcotics: Annual Prevalence