paper 14

PERIOD, AGE, AND COHORT EFFECTS ON SUBSTANCE USE AMONG AMERICAN YOUTH 1976-1982

Patrick M. O'Malley
Jerald G. Bachman
Lloyd D. Johnston

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Patrick M. O'Malley
Jerald G. Bachman
Lloyd D. Johnston

Institute for Social Research
The University of Michigan
Ann Arbor, Michigan

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Abstract

Period, age, and cohort effects on substance use among American youth 18 to 24 years old during the period from 1976 to 1982 are differentiated. The data for this report come from the Monitoring the Future project, an ongoing study of high school seniors. The study employs a cohort-sequential design, and involves nationally representative surveys of each high school senior class since 1975, plus follow-up surveys mailed each year to 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 class.

Period effects in the form of monotonic increases occurred over the interval for cocaine, amphetamines, and methaqualone, while linear decreases occurred for barbiturates, psychedelics other than LSD, and tranquilizers. Marijuana showed a curvilinear period effect, first increasing then decreasing.

Effects of age were more complex. Increases in the year after high school were seen for daily cigarette use, but not for monthly use. Monthly and daily alcohol use increased linearly with age, and monthly use also showed a curvilinear component. A measure of heavy drinking showed only a curvilinear trend, first increasing and then decreasing. A possible age effect also appeared for daily marijuana use, but this was less certainly an age effect (as opposed to a class effect). Annual use of narcotics other than heroin showed a linear age decrease.

Clear class (or cohort) effects appeared for cigarette use, with each successive class smoking less at all levels.

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 period, age, and cohort effects are really proxies for other, more fundamental factors, and that the documentation of these effects is an early step in understanding substance use.

Introduction

Monitoring the Future is an ongoing research project which has surveyed a representative national sample of high school seniors each year since 1975. In addition, the project has followed up 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 which may occur in the prevalence of illicit and licit drug use:

(1) Period effects: changes with time, reflected across all age groups (also referred to as secular trends),

(2) Age effects: developmental or maturational changes which show up consistently for all graduating classes,

(3) Cohort effects: sustained or lasting differences among different cohorts (or in the present study, graduating classes).

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 class; the "cohort" of interest is an educational cohort, i.e., 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 seven classes of 1976 through 1982, and for the seven years 1976 through 1982, along with the modal age at each data collection for each class. (We assume a modal age of 18 for all seniors.)

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 where 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-sixties to the early seventies. Since then, change has been more gradual, though still considerable; indeed, certain drugs--e.g., cocaine, PCP--have shown dramatic changes since the early seventies (Johnston, Bachman, & O'Malley, 1982). The rapid change associated with period is quite a different situation than that faced by traditional developmental analysts; in fact, Baltes (1968) has 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 quite limited (18 to 24 as of 1982), 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.

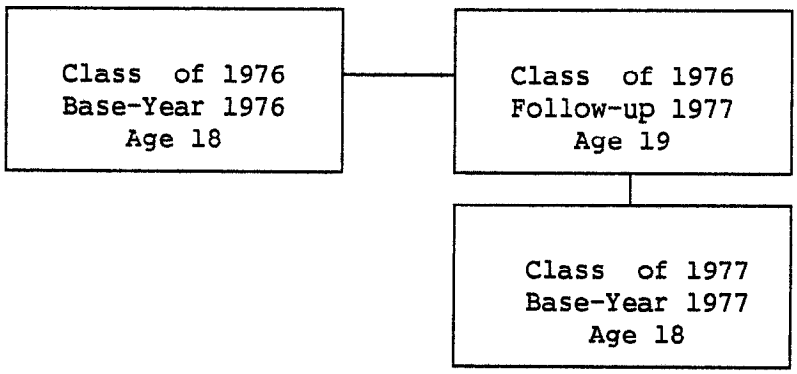
Class effects seem likely to be relatively less important than period or age in this dataset. That is, a priori, one would expect cer-

tain year effects (because cocaine use is rising, for example), and certain age effects (because most of the population is attaining legal access to alcohol). But it is more difficult to posit class effects, particularly differences between adjacent or nearly adjacent graduating classes.

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 1976-1982, we will discuss several relevant methodological topics: the general approach to cohort-sequential analysis, strategic analytic decisions which must be made, the particular modeling technique to be used here, and procedures for making best estimates of population values (which the models are intended to fit).

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 which 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 which 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 assuming 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; if there were one difference 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 which 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 28 such data cells as of 1982, rather than three. The above analytic method could be applied to all 21 triads of cells using one-year intervals, or to all 15 triads using 2-year intervals, or to the 10 triads using 3-year intervals, or to the 6 triads using 4-year intervals. This would be a rather exhaustive analysis approach, and very unparsimonious in that it imposes no constraints of ordinality, linearity or additivity. It seemed preferable to impose some such constraints at least in the initial stages of data analysis in this difficult and complex area. Mason et al. (1973) made a significant contribution to the area by showing that any constraint which removed the complete linear interdependence made the 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

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

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 Adams, 1978; Costa & McCrae, 1982; Fienberg & Mason, 1979; Pullum, 1977; Rodgers, Herzog, & Woodworth, 1980).

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 which is linear and additive, although as indicated above, all three effects could not be estimated without some additional constraints, constraints which may themselves introduce error. However, if one is willing to make 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 since 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 et al., 1976) is a specific computer program which can implement WLS.

There are other decisions which need to be made, assuming GENCAT is to be used. The dependent variables of interest here are proportions, but there is the question of 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 intui-

tively 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.[1] 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:

(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 less statistically significant.

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.

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

Modelling Technique

Assessing goodness of fit. Having chosen to use WLS to analyze proportions, the next set of 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 ($\hat{P}$) is derived. A generalized least-squares goodness-of-fit chi-square statistic is provided, which assesses the overall fit of $\hat{P}$ to P. The statistical significance of each individual parameter can also be assessed by a chi-square, as well as any combination of parameters.

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 to be very high, we run a danger of excessive Type II errors. High levels ($p > .9$) may actually involve "too good" a fit--i.e., the model may include unnecessary parameters (Knoke & Burke, 1981; Bishop et al., 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.

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 which 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. Since 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.[1]

For the measures which showed some variability, the data were displayed graphically and inspected for evidence of "pure" linear age, period, or class effects. Table B shows examples of what the data might look like for 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

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[1]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 intuitive notions and on empirical looks at the data, we believe that any probability much less than .50 leaves room for improvement of the fit.

higher than the previous. Finally, panel 3 shows class effects, but no age or year effects. Where the actual data appeared to show specific effects, a model which 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 non-linearity 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.)

Estimation of Population Values

The final 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 some from the total base-year sample due to sampling error), and panel attrition.[1]

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.[2]

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[1]Because of unacceptably low participation rates in the 1977 follow-up, the procedures were changed beginning in 1978, with the major changes being the addition of a financial incentive and a reduction in the size of the sample. Since then, response rates have been quite good, generally in excess of 80%. Thus, the attrition problem is most severe for the class of 1976 followed-up in 1977, but it exists to some extent for all the follow-up data.

[2]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 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.

This procedure was carried out for each prevalence measure for each of a number of licit and illicit substances, for each follow-up panel.[1] 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 80%), and because the financial inducement to participate probably reduces the degree to which willingness to participate varies among subgroups.

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; Johnston, Bachman, & O'Malley, 1981a, 1981b); 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 between 15,000 and 19,000 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 which will extend to ten years following graduation. From each senior class, two separate groups are selected, each 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. The class of 1976 follow-up of 1977 differed in that respondents were not paid for participation, so response rates in that year were somewhat lower. Otherwise, response rates have been over 75%. Table C provides the unweighted numbers and percent participating.

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[1]Note that since each follow-up year on a given cohort is based on a different panel on alternating years, each follow-up year is estimated separately using a separate reweighting.

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 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, amphetamine, methaqualone (quaaludes), barbiturates, LSD, psychedelics other than LSD, tranquilizers, heroin, and narcotics other than heroin.

The questions about cigarette use depart from the above 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 (none, less than 1 cigarette per day, 1-5 cigarettes per day, about 1/2 pack per day, about one pack per day, about one and a half packs per day, 2 or more packs 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 .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 which 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 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 shape 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 non-linear effects are designated in the summary table in four different ways:

(1) Quadratic effects of age and year, reflecting first an increase, and then a decrease. Coefficients were chosen to be orthogonal to linear trends.

(2) An age effect, with age 18 different from the others. In essence, this would indicate an age effect which shows up entirely in the first year after high school.

(3) An age effect, linear from age 18 to 21, and zero thereafter.

(4) A year effect, with the year 1982 being different from the others.

Because the code values 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. Some of the measures in Table D do show high values for the baseline model (i.e., LSD and heroin), and the proper inference is that they simply are not varying much over the study period.[1]

A brief discussion of the main findings for each drug follows. The data are displayed graphically in Figures 1 through 18, while Tables 1 through 18 contain the model results for the corresponding figures.

Cigarettes

Figures 1, 2, and 3 show the longitudinal trajectories for the classes of 1976-1981, followed up through 1982, plus the class of 1982; the figures show the percentages smoking cigarettes at three different levels (monthly, daily, and 1/2 pack or more per day). Figure 3 is the clearest, and we discuss it first. The top line of connected 6's 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 increased only slightly thereafter, to about 26% in 1982, when the modal age was 24. Note in Figure 3 that smoking among seniors had been showing declines since 1977 (see the left-most point on each line). In the absence of the follow-up data, this decline could be attributed to either a class effect (with members of each successive class less likely than the previous to be smokers),

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[1]The non-variation in some tables is applicable to the table as a whole. 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. For example, 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, Bachman, & O'Malley, 1982).

or a period effect (that is, everyone is smoking less). The data displayed in Figure 3 (and tabulated in Table 3) suggest strongly that there is no period effect, but rather there is a clear class effect. Note that although the senior year data show declines, 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 et al., 1982). In addition to the class effect, there is also an evident age effect, in that there is a jump in the percentage smoking in the first year after high school for all classes.

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 .982, and 91.3% 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 20.7%, 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 20.7%. There is a linear class effect of -1.4%, so that each successive class is predicted to have 1.4% fewer of such smokers than the preceding class. There is no period effect at all, but there is a non-linear age effect which indicates a jump of 4.9% in rates of half-a-pack or more smoking for all classes between ages 18 and 19 (that is, during the first year after high school graduation), and no further age-related changes. Thus, the predicted value for the class of 1980 followed up in 1982 would be:

$$20.7\% + 4(-1.4\%) + 4.9\% = 20.0\%.$$

The actual observed value, as shown in Table 3, is 20.5%; there is an error, or residual, of .5% (or .4%, as shown in Table 3, based on computations with less rounding error.)

The estimated age effect indicates a jump of nearly 5%, on the average, in the year after high school. This increase in the percentage smoking at the rate of 1/2 pack or more is due almost entirely to increased rates of smoking among respondents who as seniors were active smokers, but at lower rates. We suspect that the explanation for the increase may be the lessening of constraints inhibiting smoking behavior. High schools generally restrict the amount of time during which students may smoke, and this may be enough to explain the rise after high school.

A more inclusive measure of cigarette use--any use on a daily basis--shows a very similar pattern of a jump in the first year after high school, combined with a decline in successive classes (Figure 2). In this case, the age effect is smaller, at 3.1%, while the linear class effect is very slightly larger, at -1.6%. A still more inclusive

measure--any smoking during the prior month, but not daily--shows only a class effect of -1.5% (Figure 1).

The cohort effect, estimated at about -1.5% for all three measures, seems most likely due to the increased concern in recent years about the harmful health consequences of smoking. Why then is there not a general period effect? The data suggest that cigarette smoking may be very resistant to change; once started, the behavior is likely to continue, and we see a continuing difference between classes.

It is worth noting at this point that we are not interpreting any age, period, or class effect in any strictly causal sense. There are other factors for which age, period, and class serve as proxies, and these other factors are the causal influences. We will say more about this later in the discussion.

Alcohol

Monthly and daily use of alcohol show age effects, though the patterns are not as simple as might be expected. (Annual use of alcohol is not included here because it was essentially invariant, with prevalence rates at about 90%.) Monthly and daily use show linear increases, but superimposed on the linear trend for monthly use is a quadratic trend, that is, an early increase up to about age 21 and then a decrease. The fit for monthly use is much better than that for daily use ($p = .881$ versus .577). As Table 5 and Figure 5 indicate, however, there do not appear to be any simple or parsimonious additional factors which could account for the remaining variation. (The preponderance of negative residuals for base-year data in Table 5 suggests an age effect, 18 less than 19 and older, but incorporating such an effect does not significantly improve the model.)

The third alcohol measure--drinking five or more drinks in a row on at least one occasion in the prior two weeks--also shows a quadratic age effect, increasing through about age 21 and then declining.[1] The data for the class of 1976 are stable from age 21 to 23, and then drop sharply at age 24); the classes of 1977 and 1978 appear to peak at about age 20 or 21 and decline thereafter. The more recent classes show the increase, but it is too early for them to exhibit the downturn. This finding of an increase after high school, with a peak somewhere in the early or mid-twenties is consistent with other studies which have found that frequent heavy drinking peaks somewhere between the ages of 18 and 24 or 25 (Blane, 1979). A few more years of data will help to show just where that peak in "binge" or "party" drinking occurs.

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[1]It should be noted that data on age 23 are available from only two classes and in two years; and data on age 24 are available from only one class and only one year. Thus the age estimates are more tentative for later ages. Similarly, year effects for the earliest years are based on the fewest data points (cohorts), as are the class effects for the later classes, and thus are the more tentative estimates.

Marijuana

All three measures of marijuana show very similar curvilinear secular trends--early increases up to about 1978 or 1979, followed by recent declines. This strong secular trend, expressed in Table D in quadratic form, is the major effect for annual and monthly use; probabilites are .874 and .928, respectively. The daily use measure shows a less close fit; the nominal probability is only .455 that the quadratic function is an accurate representation of the underlying reality. Clearly, there is room for some additional effect or effects. However, the nature of that additional effect (or effects) is ambiguous.

The ambiguity is partly a function of the specific shape of the fitted secular trend. If one constrains that shape to be quadratic in form, then an additional linear class effect offers a significant improvement in fit, and the class effect is clearly better than an age effect. However, if one chooses to leave the year effect unconstrained, then either a linear age or a linear class effect would result in a significantly improved fit; furthermore, the age or class effect would improve the fit equally well, and there is no statistical way to choose between them. The class effect would be negative, while the age effect would be positive (and equal in absolute value).

In other words, imposition of a strong assumption--a specific quadratic year effect--leads to a conclusion that there is a negative linear class effect operating. On the other hand, imposition of a completely unconstrained year effect results in a condition wherein a distinction between an additional linear class or age effect is impossible.[1]

If there were clear reasons to prefer either the unconstrained secular trend or the quadratic shape, then the ambiguity might be reduced. The unconstrained model provides a very slightly better fit than the quadratic (probabilities equal to .552 and .455, respectively), but the two are basically quite similar. We are thus left with an ambiguous case, and there is no compelling reason to choose one interpretation over any of several others. Our general orientation is to expect age effects to be more common than class effects in the area of substance use; consequently, Table D indicates a fitted model that includes a quadratic year effect, plus a linear age effect. (The quadratic effect is selected because it is more parsimonious, using only one degree of freedom and imposing some regularity in the model.) Although the data are quite consistent with several other alternative explanations, one thing is very clear: the dominant effect in the data is a strong secular trend in daily marijuana use. The shape of this trend is certainly an initial increase and a later decrease, although the form may not be specifically quadratic. In addition, there is either a negative class effect or a positive age effect (very likely approximately linear in both cases), or some combination of both. As shown in Table

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[1]An unconstrained year effect combined with an unconstrained class or age effect sheds little light; they are equally successful at fitting the data.

D, the age effect is likely to be moderate, +0.4%. (As an example of the relative strengths of the effects, the differences in predicted scores for the ages of 18 and 21 is 1.2% for daily use, while the corresponding difference in predicted scores for the years 1976 and 1979 is 3.6%.)

Illicit Drugs Other Than Marijuana

Cocaine use rose dramatically during the last half of the 1970's. One can see in Figure 10 that usage rates went from a low of 6% among seniors in 1976 to over 20% for those over 21 in the early 1980's. There seemed to be a levelling among seniors between 1979 and 1980, and most age levels showed only slight increases (and in one case a slight decrease) between 1980 and 1981. However, there were subsequent increases in prevalence rates between 1981 and 1982 for all age groups except the seniors. A rather simple model, while not incorporating all these complexities, can explain the data fairly well; this "simple" model includes only a linear effect for year (+1.4% per year) and a non-linear effect for age (+2.9% per year up through age 21 with no age-related change thereafter).[1] The fit is only fair, and could obviously be improved by adding interaction effects to reflect the possibly different trends occurring among the seniors (and perhaps among the 19-year old group as well). However, this would add considerable complexity; at this time it seems preferable to wait for data from an additional year or two to clarify whether differential trends are in fact occurring.

Amphetamine use showed substantial increases from 1978 through 1981, increasing about 2.2% per year. As Figure 11 shows, there was a general decline in 1982, and a parameter to incorporate that decline significantly improves the fit. However, rather than reflecting any real change in amphetamine use, the 1982 decline is primarily due to a methodological change in the way that respondents are asked about their use of amphetamines. 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 follow-up surveys; thus, the change in prevalence appears due to the change in the questions.

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[1]An age effect linear between 18 and 24 was not very useful; instead, the pattern of residuals suggested a linear age effect up to age 21 and no age effect thereafter. The rise in cocaine use evident in Figure 10 for ages 22, 23, and 24 is better explained by the linear year effect than by an additional age effect.

The figure for methaqualone, one of the two types of sedatives under study, shows an increasing secular trend (+0.7%). This effect describes the data fairly well ($p = .683$), and there do not appear to be any simple age or class effects operating.

Barbiturates, the other type of sedative, also show an apparent secular trend, but in the opposite direction-- a decrease in use with time (-0.7% per year).

The hypothesis that the data for LSD could have been generated by chance factors (other than a constant) cannot be rejected ($p = .983$).

For psychedelics other than LSD and for tranquilizers there are downward secular trends of -0.5% and -0.6%, respectively.

The use of heroin shows a high likelihood that observed variation left after fitting a constant is due to chance factors ($p = .956$). Narcotics other than heroin show a slight linear decrease with age (-0.3%).

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 1982. Period effects in the form of monotonic increases have occurred over that interval for cocaine, amphetamines, and methaqualone, while linear decreases have occurred for barbiturates, psychedelics other than LSD, and tranquilizers. Marijuana showed a curvilinear period effect, first increasing and then decreasing.

Effects of age were more complex. Increases in the year after high school were seen for daily cigarette use (any daily use and use of 1/2 pack or more per day), but not for monthly cigarette use, indicating that there were not more 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 increased linearly with age, and the monthly use also included a quadratic component. A measure of "binge" drinking showed only a quadratic trend (first increasing, then decreasing). A possible age effect also appeared for daily marijuana use, but this was less clearly an age effect (as opposed to a class effect). Annual use of narcotics other than heroin showed a linear age decrease.

Clear class effects appeared for cigarette use, with each successive class smoking less at all levels.

Discussion

The period effects reported in the results section are generally quite consistent with our previous reports based on senior year data only (e.g., Johnston et al., 1982). For example, marijuana use had been increasing and more lately 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 more recent decrease. The cohort-sequential design permits a different, and we believe more accurate, interpretation of this pattern as being a class effect, rather than a period effect. Cocaine use also showed a pattern of change among seniors which is not entirely representative of the pattern in the full design. Senior data in recent years indicated a reduction in use, suggesting a period effect. The cohort-sequential data suggest that this may not be the case, because other age levels showed no such decrease. It is clear that 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 which 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 which change over time in the physical or social environment and which 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 (e.g., 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 is not 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, and 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 im-

portant social role transition is graduation from high school, and we see a clear effect of this transition on the frequency of cigarette use. Other important role transitions which 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 et al., 1978; Bachman et al., 1981; 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 (Bachman et al., 1981), 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 straight-forward in their interpretations. In one sense, they are interactions between year (or period) effects and age effects; that is, they are period effects which affect only some age groups.[1] For example, cohorts that were of wage-earning age during the Great Depression of the 1930's are hypothesized to have been affected differently than other cohorts. But the Great Depression itself was clearly a period phenomenon--the decade of the 1930's. Another example: the "baby boom" cohorts was 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, cognitions, and emotions 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 nineteen-seventies, as new and more damaging evidence was accumulated

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[1]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).

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, Bachman, and O'Malley, 1982).

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. One of the more interesting next steps is to disaggregate the data. 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). 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
1976	**18**	19	20	21	22	23	24
1977		**18**	19	20	21	22	23
1978			**18**	19	20	21	22
1979				**18**	19	20	21
1980					**18**	19	20
1981						**18**	19
1982							**18**

Notes:

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

Table B

Examples of Data Showing "Pure" Effects

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1. Age Effects							
1976	.10	.15	.20	.25	.30	.35	.40
1977		.10	.15	.20	.25	.30	.35
1978			.10	.15	.20	.25	.30
1979				.10	.15	.20	.25
1980					.10	.15	.20
1981						.10	.15
1982							.10
2. Year Effects							
1976	.10	.15	.20	.25	.30	.35	.40
1977		.15	.20	.25	.30	.35	.40
1978			.20	.25	.30	.35	.40
1979				.25	.30	.35	.40
1980					.30	.35	.40
1981						.35	.40
1982							.40
3. Class Effects							
1976	.10	.10	.10	.10	.10	.10	.10
1977		.15	.15	.15	.15	.15	.15
1978			.20	.20	.20	.20	.20
1979				.25	.25	.25	.25
1980					.30	.30	.30
1981						.35	.35
1982							.40

Table C

Number of Cases

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976							
Participated	2224	1360	887	841	904	862	875
Percent	100%	61.2%	79.8%	75.6%	81.3%	77.5%	78.7%
1977							
Participated		2360	1008	973	963	974	940
Percent		100%	85.4%	82.5%	81.6%	82.5%	79.7%
1978							
Participated			2410	1008	1015	996	980
Percent			100%	83.7%	84.2%	82.7%	81.3%
1979							
Participated				2434	1051	1001	983
Percent				100%	86.4%	82.3%	80.8%
1980							
Participated					2500	1056	1016
Percent					100%	86.2%	81.3%
1981							
Participated						2458	1026
Percent						100%	83.5%

Notes:

"Participated" refers in the base-year entries to the number of cases selected for follow-up; in follow-up entries it refers to the number of participants.

"Percent" is based on respondents who were originally selected for the follow-up (half in even years and half in odd years, starting in 1978).

Table D: Summary Table of Effects

Prevalence Measure	Significant Effects				Probability of Model		Percent Error Reduction
	Constant	Year	Age	Class	Constant Only	Fitted Model	
1. Monthly Cigarette	39.1			-1.5	.000	.897	70.7%
2. Daily Cigarette (any) . .	29.5		3.1[1]	-1.6	.000	.997	89.9%
3. Daily Cigarette (1/2pack)	20.7		4.9[1]	-1.4	.000	.982	91.3%
4. Monthly Alcohol	74.2		1.0[2]		.000	.881	83.9%
5. Daily Alcohol	6.4		0.6		.027	.577	44.2%
6. 2 Weeks Alcohol 5Drinks .	42.1		Q		.433	.980	51.5%
7. Annual Marijuana	49.0	Q			.013	.874	60.8%
8. Monthly Marijuana	34.6	Q			.000	.928	75.2%
9. Daily Marijuana	8.4	Q	0.4		.003	.764	61.7%
10. Annual Cocaine	5.7	1.4	2.9[3]		.000	.697	94.1%
11. Annual Amphetamine . . .	14.6	2.2[4]			.000	.714	78.4%
12. Annual Methaqualone . . .	4.3	0.7			.000	.683	63.0%
13. Annual Barbiturate . . .	8.5	-0.7			.006	.862	62.5%
14. Annual LSD	6.9				.983	.983	0.0%
15. Annual Psychedelics . . .	7.9	-0.5			.073	.852	51.4%
16. Annual Tranquilizer . . .	11.1	-0.6			.045	.845	53.7%
17. Annual Heroin	0.3				.956	.956	0.0%
18. Annual Narcotics	5.5		-0.3		.306	.667	25.8%

Notes: Q = Quadratic effect (increasing then decreasing).
[1]Age: 18 ≠ 19-24.

Table 1

Cigarettes: Monthly Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	38.8	39.3	39.0	40.5	35.7	38.6	36.7
Residual	*-0.3*	*0.2*	*-0.1*	*1.4*	*-3.4*	*-0.5*	*-2.4*
1977:Observed		38.4	37.2	39.2	38.3	36.3	35.5
Residual		*0.8*	*-0.4*	*1.6*	*0.7*	*-1.3*	*-2.1*
1978:Observed			36.7	39.4	39.4	37.1	37.4
Residual			*0.6*	*3.3*	*3.2*	*1.0*	*1.3*
1979:Observed				34.4	33.6	36.4	36.4
Residual				*-0.2*	*-1.0*	*1.8*	*1.8*
1980:Observed					30.5	33.8	31.0
Residual					*-2.6*	*0.7*	*-2.1*
1981:Observed						29.4	32.8
Residual						*-2.2*	*1.2*
1982:Observed							30.0
Residual							*-0.1*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 17.40 with 26 degrees of freedom, P = 0.897.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	39.1
Class	-1.5

Table 2

Cigarettes: Daily Prevalence(any)

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	28.8	30.5	32.6	31.8	31.3	31.2	32.0
Residual	-0.7	-2.1	0.1	-0.8	-1.3	-1.4	-0.6
1977:Observed		28.8	30.1	32.0	31.9	33.2	30.7
Residual		0.9	-0.9	1.0	1.0	2.2	-0.3
1978:Observed			27.5	31.5	31.3	30.0	30.1
Residual			1.2	2.2	1.9	0.6	0.8
1979:Observed				25.4	28.5	27.6	28.9
Residual				0.7	0.8	-0.2	1.1
1980:Observed					21.4	24.9	25.4
Residual					-1.7	-1.3	-0.8
1981:Observed						20.3	23.3
Residual						-1.2	-1.3
1982:Observed							21.1
Residual							1.2

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 10.07 with 25 degrees of freedom, P = 0.997.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	29.5
Age (18 ≠ 19-24)	3.1
Class	-1.6

Table 3

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

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	19.2	24.0	24.8	26.9	25.2	25.9	26.3
Residual	-1.5	-1.6	-0.8	1.3	-0.4	0.3	0.7
1977:Observed		19.4	22.8	24.9	24.9	25.4	23.8
Residual		0.1	-1.4	0.7	0.7	1.2	-0.4
1978:Observed			18.8	24.1	23.0	24.5	24.6
Residual			0.9	1.2	0.1	1.6	1.8
1979:Observed				16.5	21.3	19.6	23.3
Residual				-0.1	-0.1	-1.9	1.8
1980:Observed					14.3	17.2	20.5
Residual					-0.9	-2.9	0.4
1981:Observed						13.5	18.1
Residual						-0.3	-0.7
1982:Observed							14.2
Residual							1.7

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 12.48 with 25 degrees of freedom, P = 0.982.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	20.7
Age (18 ≠ 19-24)	4.9
Class	-1.4

Table 4

Alcohol: Monthly Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	68.3	72.4	76.8	76.9	77.3	79.2	77.5
Residual	-2.7	-2.7	-1.3	-2.9	-2.9	-0.1	0.3
1977:Observed		71.2	76.5	77.1	81.7	81.1	79.9
Residual		0.2	1.3	-1.1	1.9	0.9	0.6
1978:Observed			72.1	76.2	78.5	79.7	79.7
Residual			1.1	1.0	0.3	-0.1	-0.5
1979:Observed				71.8	76.8	78.8	82.1
Residual				0.8	1.6	0.7	2.4
1980:Observed					72.0	77.0	77.8
Residual					1.0	1.8	-0.3
1981:Observed						70.7	73.7
Residual						-0.3	-1.5
1982:Observed							69.7
Residual							-1.3

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 17.02 with 25 degrees of freedom, P = 0.881.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	74.2
Age	1.0
Age (Quadratic)	0.6

Table 5

Alcohol: Daily Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	5.6	5.8	8.1	10.0	9.2	8.5	10.4
Residual	*-0.8*	*-1.1*	*0.6*	*2.0*	*0.5*	*-0.7*	*0.7*
1977:Observed		6.1	7.7	8.6	8.4	7.0	8.0
Residual		*-0.3*	*0.8*	*1.1*	*0.4*	*-1.6*	*-1.2*
1978:Observed			5.7	7.9	7.0	8.3	7.0
Residual			*-0.7*	*1.0*	*-0.5*	*0.2*	*-1.6*
1979:Observed				6.9	8.6	8.3	11.7
Residual				*0.5*	*1.7*	*0.8*	*3.6*
1980:Observed					6.0	6.1	6.8
Residual					*-0.4*	*-0.8*	*-0.7*
1981:Observed						6.0	8.3
Residual						*-0.4*	*1.4*
1982:Observed							5.7
Residual							*-0.6*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 23.98 with 26 degrees of freedom, P = 0.577.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	6.4
Age	0.6

Table 6

Alcohol: 2 Weeks Prevalence(5+ drinks)

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	37.1	39.4	41.6	42.6	42.3	42.6	37.0
Residual	*-3.1*	*-2.7*	*-0.5*	*0.5*	*0.2*	*0.5*	*-5.1*
1977:Observed		39.4	44.1	44.7	43.9	41.2	41.5
Residual		*-0.8*	*0.9*	*1.5*	*0.7*	*-2.0*	*-1.7*
1978:Observed			40.3	42.5	45.7	45.6	42.6
Residual			*0.1*	*-1.1*	*2.2*	*2.0*	*-1.0*
1979:Observed				41.2	43.1	44.6	44.7
Residual				*1.0*	*-0.1*	*1.4*	*1.5*
1980:Observed					41.2	42.0	42.2
Residual					*1.0*	*-0.1*	*0.1*
1981:Observed						41.4	43.9
Residual						*1.2*	*3.6*
1982:Observed							40.5
Residual							*0.3*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 18.10 with 26 degrees of freedom, P = 0.872.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	42.1
Age (Quadratic)	0.5

Table 7

Marijuana: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	44.5	48.4	53.2	52.4	49.4	45.7	45.4
Residual	-1.2	-0.5	2.3	0.9	-1.5	-3.3	-0.3
1977:Observed		47.6	53.8	52.0	52.2	51.8	48.2
Residual		-1.4	2.9	0.5	1.3	2.8	2.5
1978:Observed			50.2	51.5	50.2	50.6	44.5
Residual			-0.7	-0.1	-0.7	1.6	-1.2
1979:Observed				50.8	50.1	51.6	49.4
Residual				-0.7	-0.8	2.6	3.6
1980:Observed					48.8	47.8	45.1
Residual					-2.1	-1.2	-0.7
1981:Observed						46.1	45.4
Residual						-2.9	-0.3
1982:Observed							44.3
Residual							-1.4

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 18.06 with 26 degrees of freedom, P = 0.874.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	49.0
Year (Quadratic)	0.6

Table 8

Marijuana: Monthly Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	32.2	35.8	38.3	38.6	37.9	33.4	32.2
Residual	1.7	1.3	1.4	0.9	0.9	-1.2	1.7
1977:Observed		35.4	38.6	41.4	36.1	37.9	30.9
Residual		0.8	1.6	3.6	-0.9	3.3	0.4
1978:Observed			37.1	37.7	36.7	33.3	30.5
Residual			0.1	-0.1	-0.3	-1.3	0.0
1979:Observed				36.5	35.5	34.8	31.6
Residual				-1.3	-1.5	0.2	1.0
1980:Observed					33.7	33.0	29.8
Residual					-3.3	-1.6	-0.7
1981:Observed						31.6	29.8
Residual						-3.0	-0.7
1982:Observed							28.5
Residual							-2.0

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 16.33 with 26 degrees of freedom, P = 0.928.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	34.6
Year (Quadratic)	0.8

Table 9

Marijuana: Daily Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	8.2	10.0	11.7	12.7	12.2	9.6	9.9
Residual	-0.6	-0.2	0.7	1.4	1.2	-0.6	1.0
1977:Observed		9.1	10.1	11.6	10.1	10.4	7.7
Residual		-0.6	-0.4	0.8	-0.4	0.7	-0.6
1978:Observed			10.7	11.0	9.3	8.2	7.3
Residual			0.7	0.7	-0.6	-0.9	-0.5
1979:Observed				10.3	8.2	8.2	6.7
Residual				0.6	-1.3	-0.4	-0.5
1980:Observed					9.1	6.9	8.6
Residual					0.2	-1.2	1.9
1981:Observed						7.0	6.8
Residual						-0.6	0.6
1982:Observed							6.3
Residual							0.7

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 11.44 with 25 degrees of freedom, P = 0.990.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	8.4
Year (Quadratic)	0.4
Age	0.4

Table 10

Cocaine: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	6.0	8.9	12.7	18.7	20.1	21.7	22.9
Residual	0.3	-1.2	-1.7	0.0	0.0	0.2	0.1
1977:Observed		7.2	10.8	15.8	19.6	20.9	25.4
Residual		0.1	-0.7	0.1	-0.5	-0.6	2.5
1978:Observed			9.0	13.3	19.0	18.9	21.8
Residual			0.5	0.5	1.9	-2.6	-1.1
1979:Observed				12.0	15.6	18.3	26.4
Residual				2.1	1.4	-0.2	3.5
1980:Observed					12.3	14.1	22.2
Residual					1.0	-1.5	2.3
1981:Observed						12.4	15.8
Residual						-0.2	-1.2
1982:Observed							11.5
Residual							-2.5

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 20.91 with 25 degrees of freedom, P = 0.697.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	5.7
Year	1.4
Age (Linear to 21, constant thereafter)	2.9

Table 11

Amphetamine: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	15.8	18.0	19.4	24.2	26.2	26.5	22.8
Residual	1.2	1.2	0.3	2.9	2.7	0.7	-1.9
1977:Observed		16.3	17.0	21.8	24.5	25.5	23.2
Residual		-0.5	-2.0	0.5	1.0	-0.3	-1.5
1978:Observed			17.1	21.7	24.8	26.4	25.0
Residual			-1.9	0.5	1.3	0.6	0.3
1979:Observed				18.3	23.3	25.3	25.0
Residual				-3.0	-0.2	-0.5	0.3
1980:Observed					20.8	25.2	28.3
Residual					-2.7	-0.6	3.6
1981:Observed						26.0	23.3
Residual						0.2	-1.5
1982:Observed							26.1
Residual							1.4

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 20.61 with 25 degrees of freedom, P = 0.714.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	14.6
Year	2.2
Year (1976-1981 ≠ 1982)	-3.3

Table 12

Methaqualone: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	4.7	5.1	5.0	7.3	8.5	8.7	7.0
Residual	*0.4*	*0.1*	*-0.8*	*0.8*	*1.3*	*0.8*	*-1.6*
1977:Observed		5.2	5.4	6.2	7.8	8.9	9.6
Residual		*0.2*	*-0.4*	*-0.3*	*0.6*	*1.0*	*0.9*
1978:Observed			4.9	6.2	7.4	11.2	7.4
Residual			*-0.9*	*-0.3*	*0.2*	*3.3*	*-1.3*
1979:Observed				5.9	7.8	8.5	10.7
Residual				*-0.6*	*0.6*	*0.6*	*2.1*
1980:Observed					7.2	7.2	9.9
Residual					*0.0*	*-0.7*	*1.2*
1981:Observed						7.6	7.4
Residual						*-0.3*	*-1.3*
1982:Observed							6.8
Residual							*-1.9*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 22.11 with 26 degrees of freedom, P = 0.683.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	4.3
Year	0.7

Table 13

Barbiturate: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	9.6	7.6	5.2	7.4	5.0	5.6	4.0
Residual	*1.1*	*-0.2*	*-2.0*	*0.9*	*-0.8*	*0.4*	*-0.5*
1977:Observed		9.3	6.4	7.2	5.3	6.2	3.9
Residual		*1.5*	*-0.8*	*0.7*	*-0.5*	*1.0*	*-0.6*
1978:Observed			8.1	5.3	5.4	4.9	4.9
Residual			*0.9*	*-1.2*	*-0.5*	*-0.3*	*0.4*
1979:Observed				7.5	5.7	5.1	4.8
Residual				*1.0*	*-0.2*	*-0.1*	*0.3*
1980:Observed					6.8	4.3	5.1
Residual					*0.9*	*-0.9*	*0.6*
1981:Observed						6.6	4.0
Residual						*1.4*	*-0.5*
1982:Observed							5.5
Residual							*1.0*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 18.37 with 26 degrees of freedom, P = 0.862.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	8.5
Year	-0.7

Table 14

LSD: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	6.4	6.7	6.9	8.3	7.8	6.8	6.1
Residual	-0.5	-0.2	0.0	1.4	0.9	-0.1	-0.9
1977:Observed		5.5	6.1	8.2	8.3	7.4	6.8
Residual		-1.4	-0.9	1.3	1.3	0.5	-0.1
1978:Observed			6.3	7.7	7.3	8.3	6.4
Residual			-0.6	0.8	0.4	1.4	-0.6
1979:Observed				6.6	6.8	6.6	7.6
Residual				-0.3	-0.2	-0.3	0.6
1980:Observed					6.5	6.5	8.6
Residual					-0.4	-0.4	1.7
1981:Observed						6.5	7.3
Residual						-0.4	0.3
1982:Observed							6.1
Residual							-0.8

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 13.82 with 27 degrees of freedom, P = 0.983.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	6.9

Table 15

Psychedelics: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	7.0	6.9	7.2	7.2	6.0	4.1	3.0
Residual	-0.9	-0.5	0.3	0.8	0.1	-1.2	-1.8
1977:Observed		6.9	7.1	8.0	5.2	6.8	4.7
Residual		-0.5	0.2	1.7	-0.6	1.5	-0.1
1978:Observed			7.3	6.8	6.0	5.9	6.3
Residual			0.4	0.5	0.1	0.6	1.5
1979:Observed				6.8	5.7	4.8	4.9
Residual				0.4	-0.2	-0.5	0.1
1980:Observed					6.2	4.7	5.9
Residual					0.3	-0.6	1.1
1981:Observed						5.6	5.7
Residual						0.3	0.9
1982:Observed							4.7
Residual							-0.1

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 18.61 with 26 degrees of freedom, P = 0.852.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	7.9
Year	-0.5

Table 16

Tranquilizer: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	10.3	10.4	8.2	10.1	8.8	10.6	9.2
Residual	-0.8	-0.1	-1.6	0.9	0.3	2.7	2.0
1977:Observed		10.8	9.7	10.0	7.5	8.2	7.6
Residual		0.4	-0.1	0.8	-1.0	0.3	0.4
1978:Observed			9.9	10.0	10.3	6.2	6.6
Residual			0.1	0.9	1.9	-1.7	-0.6
1979:Observed				9.6	8.2	7.9	8.1
Residual				0.5	-0.3	0.0	0.9
1980:Observed					8.7	7.3	6.0
Residual					0.2	-0.6	-1.2
1981:Observed						8.0	5.9
Residual						0.1	-1.3
1982:Observed							7.0
Residual							-0.2

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 18.81 with 26 degrees of freedom, P = 0.845.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	11.1
Year	-0.6

Table 17

Heroin: Annual Prevalence

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

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 15.83 with 27 degrees of freedom, P = 0.956.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	0.3

Table 18

Narcotics: Annual Prevalence

Class Year	Year of Data Collection						
	1976	1977	1978	1979	1980	1981	1982
1976:Observed	5.7	4.9	4.3	5.9	4.9	3.6	3.9
Residual	*0.2*	*-0.3*	*-0.6*	*1.3*	*0.6*	*-0.4*	*0.1*
1977:Observed		6.4	5.4	5.0	5.5	4.9	5.2
Residual		*0.9*	*0.2*	*0.1*	*0.9*	*0.6*	*1.1*
1978:Observed			6.0	4.0	5.9	4.8	2.7
Residual			*0.5*	*-1.1*	*1.0*	*0.2*	*-1.6*
1979:Observed				6.2	4.5	4.8	4.4
Residual				*0.7*	*-0.7*	*-0.1*	*-0.2*
1980:Observed					6.3	4.8	6.6
Residual					*0.8*	*-0.4*	*1.7*
1981:Observed						5.9	3.5
Residual						*0.4*	*-1.7*
1982:Observed							5.3
Residual							*-0.2*

Notes:

In each cell, the first entry is the observed prevalence; the second entry (in italics) is the residual value, the observed value minus the value predicted by the fitted model.

Chi-square = 22.40 with 26 degrees of freedom, P = 0.667.

Fitted model (all effects linear except as noted):

Effect	Parameter
Constant	5.5
Age	-0.3

Figure 1

Cigarettes: Monthly Prevalence

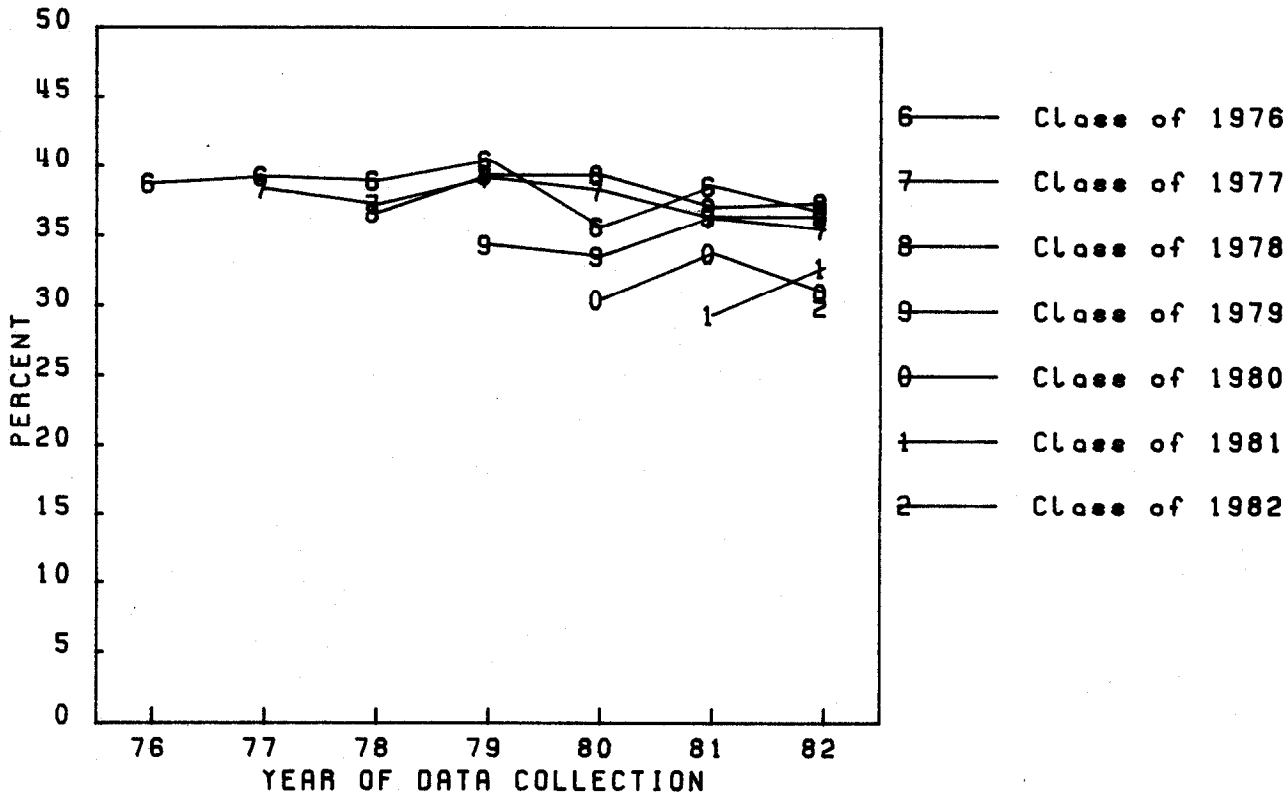

Figure 2

Cigarettes: Daily Prevalence(any)

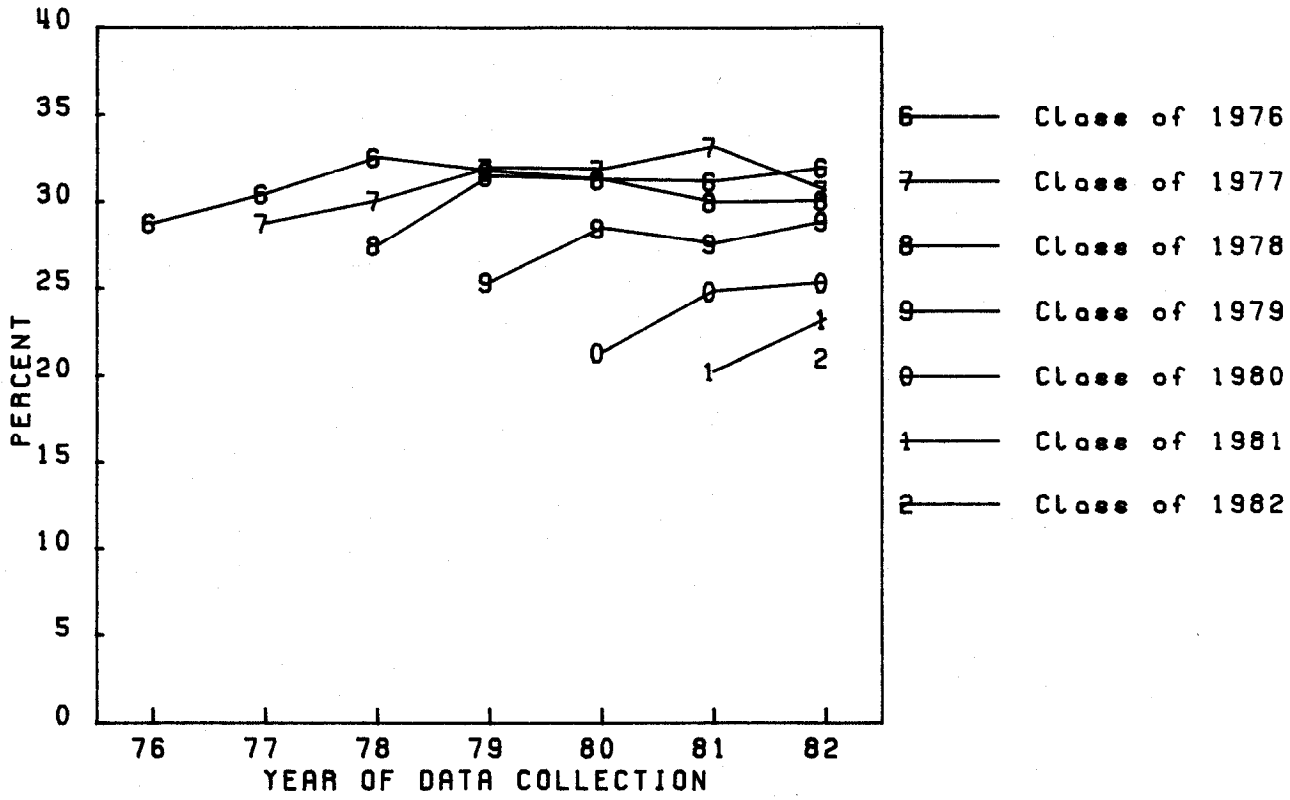

Figure 3

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

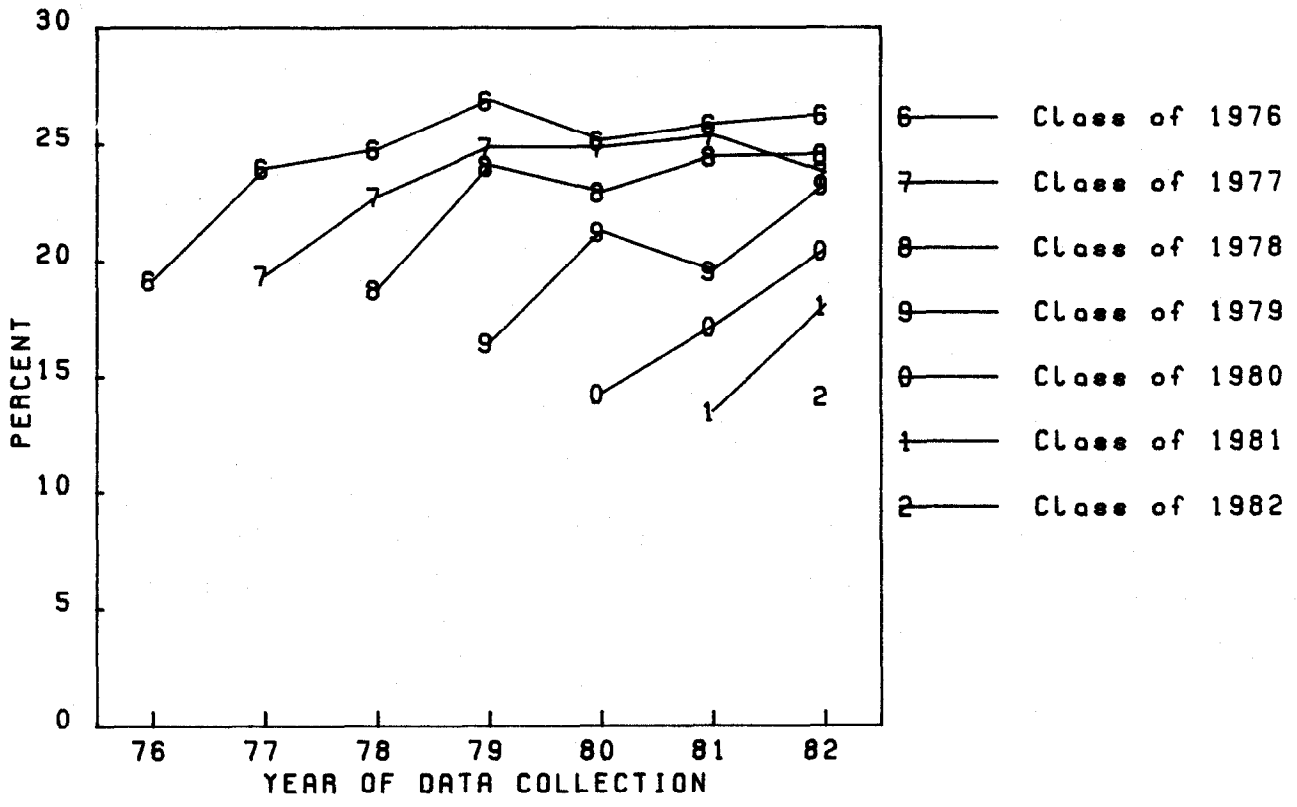

Figure 4

Alcohol: Monthly Prevalence

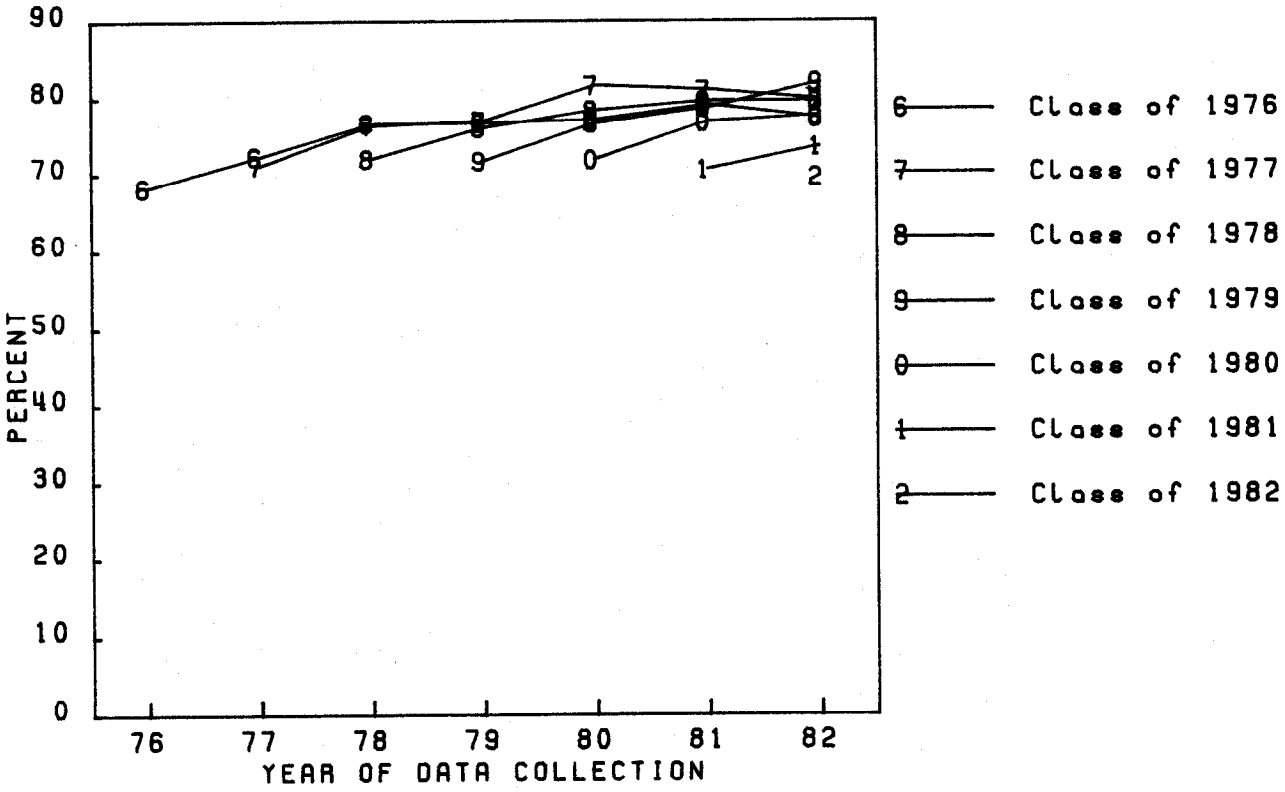

Figure 5

Alcohol: Daily Prevalence

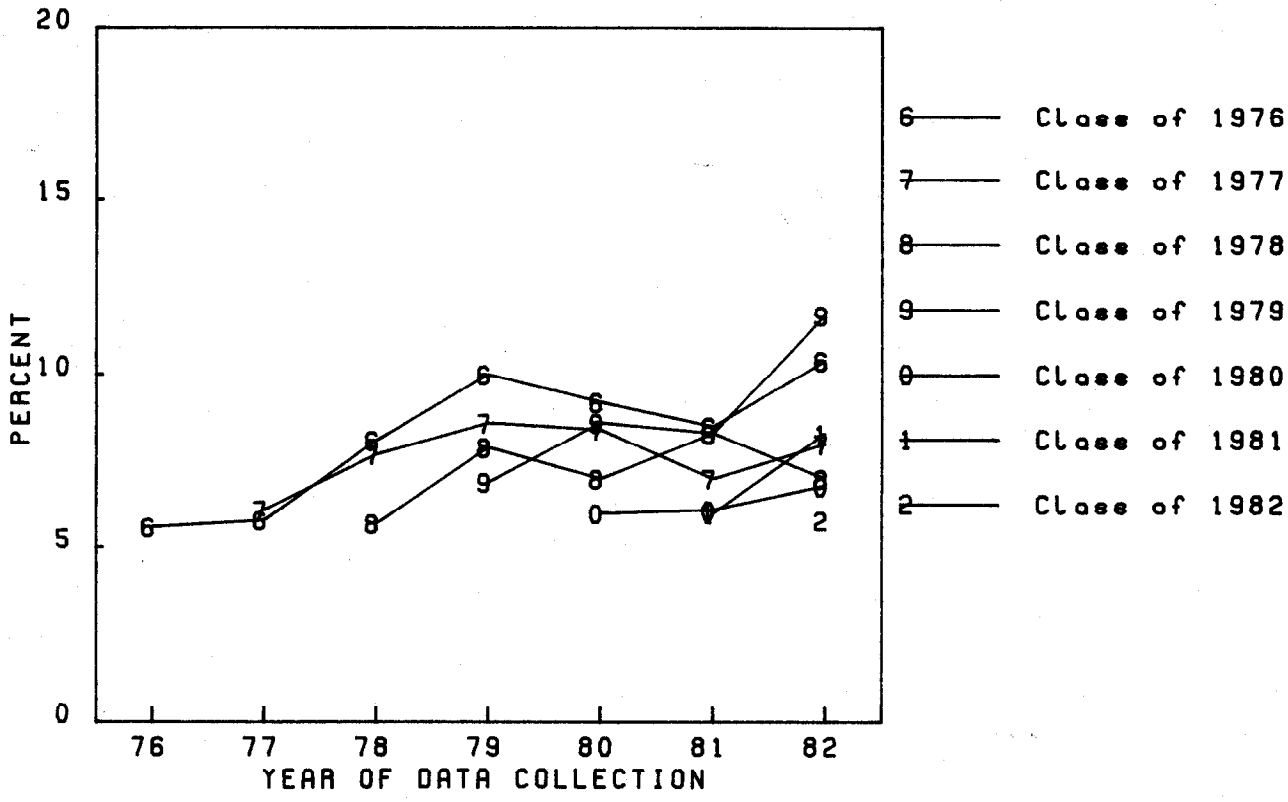

Figure 6

Alcohol: 2 Weeks Prevalence(5+ drinks)

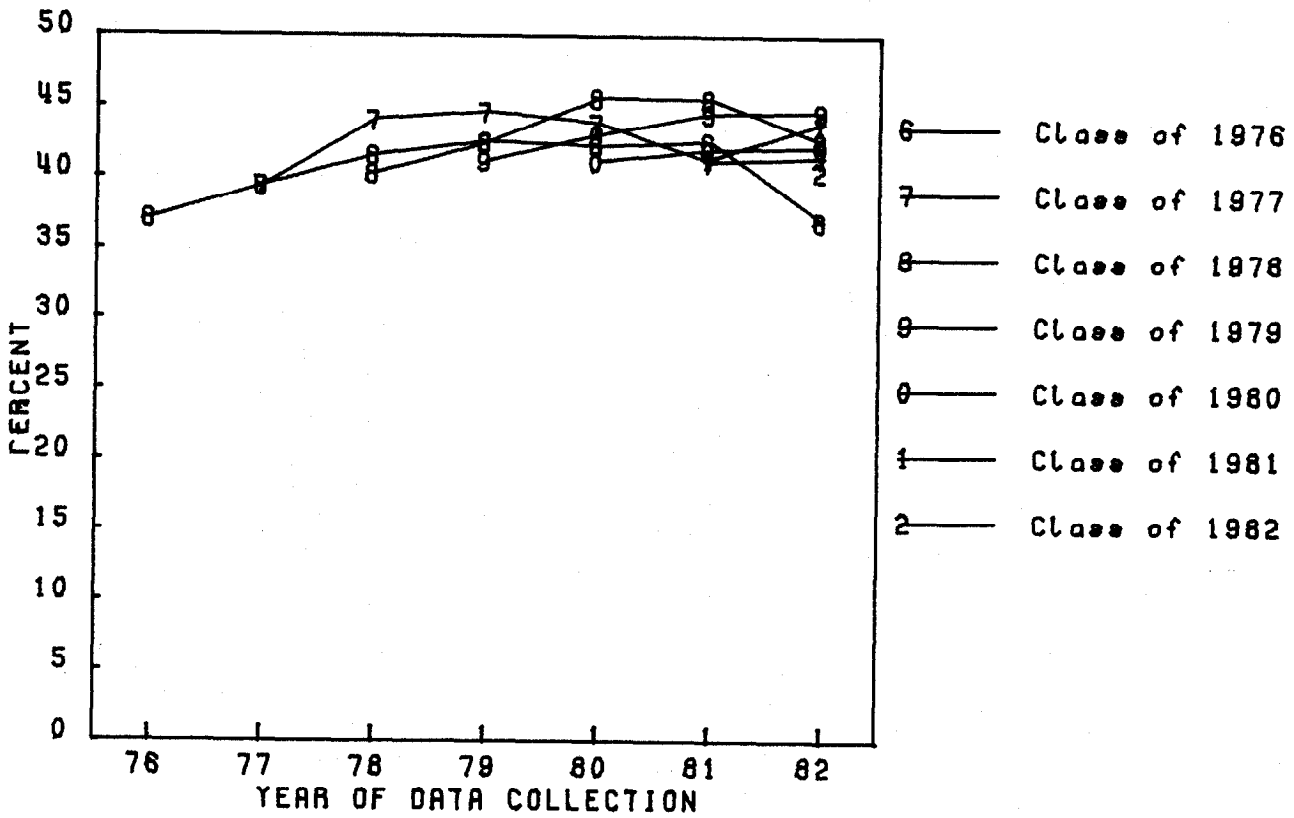

Figure 7

Marijuana: Annual Prevalence

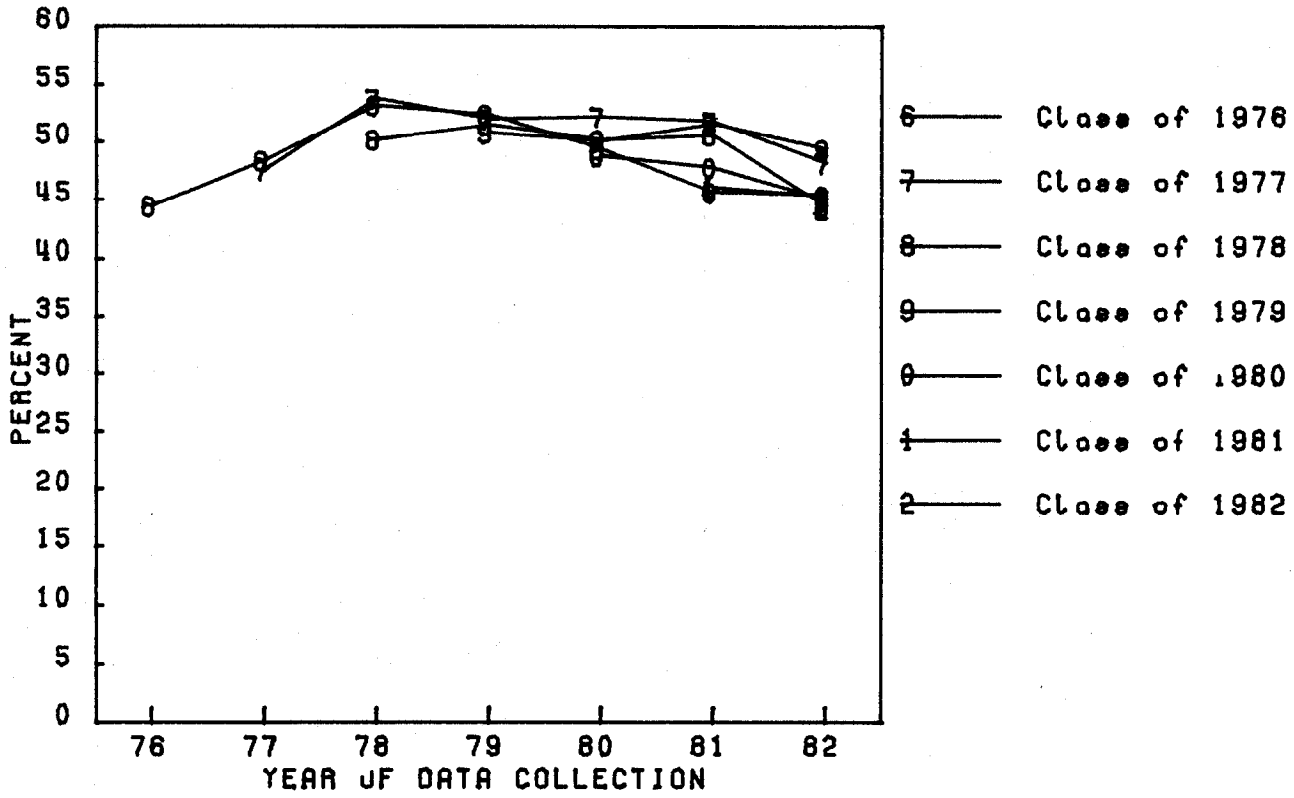

Figure 8

Marijuana: Monthly Prevalence

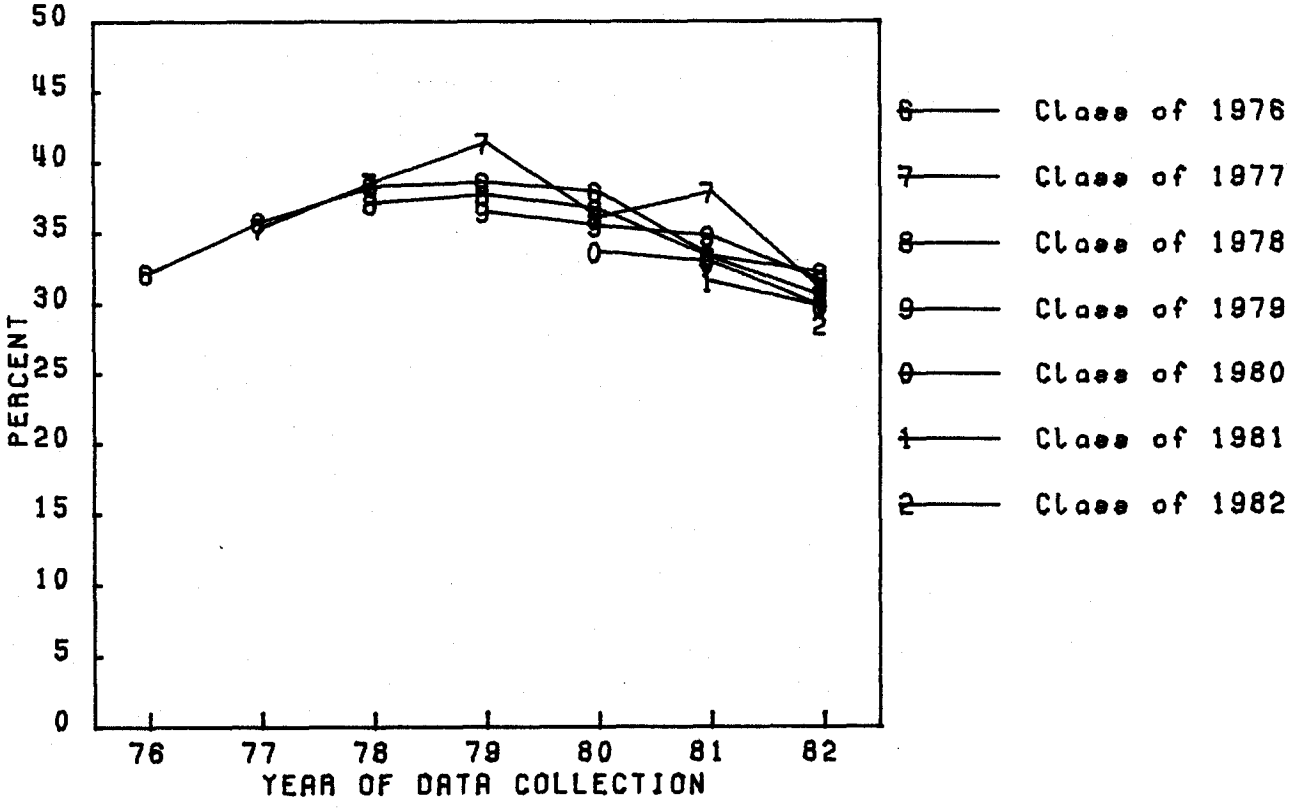

Figure 9

Marijuana: Daily Prevalence

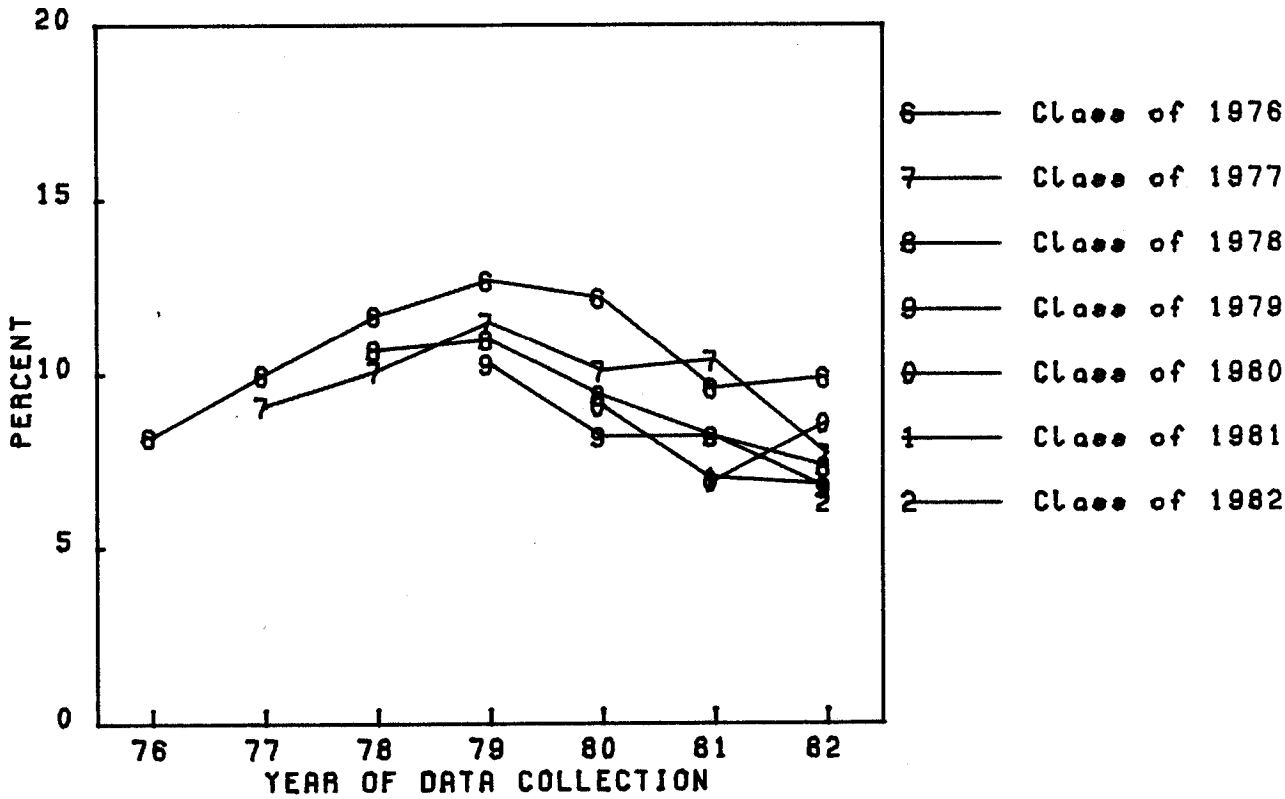

Figure 10

Cocaine: Annual Prevalence

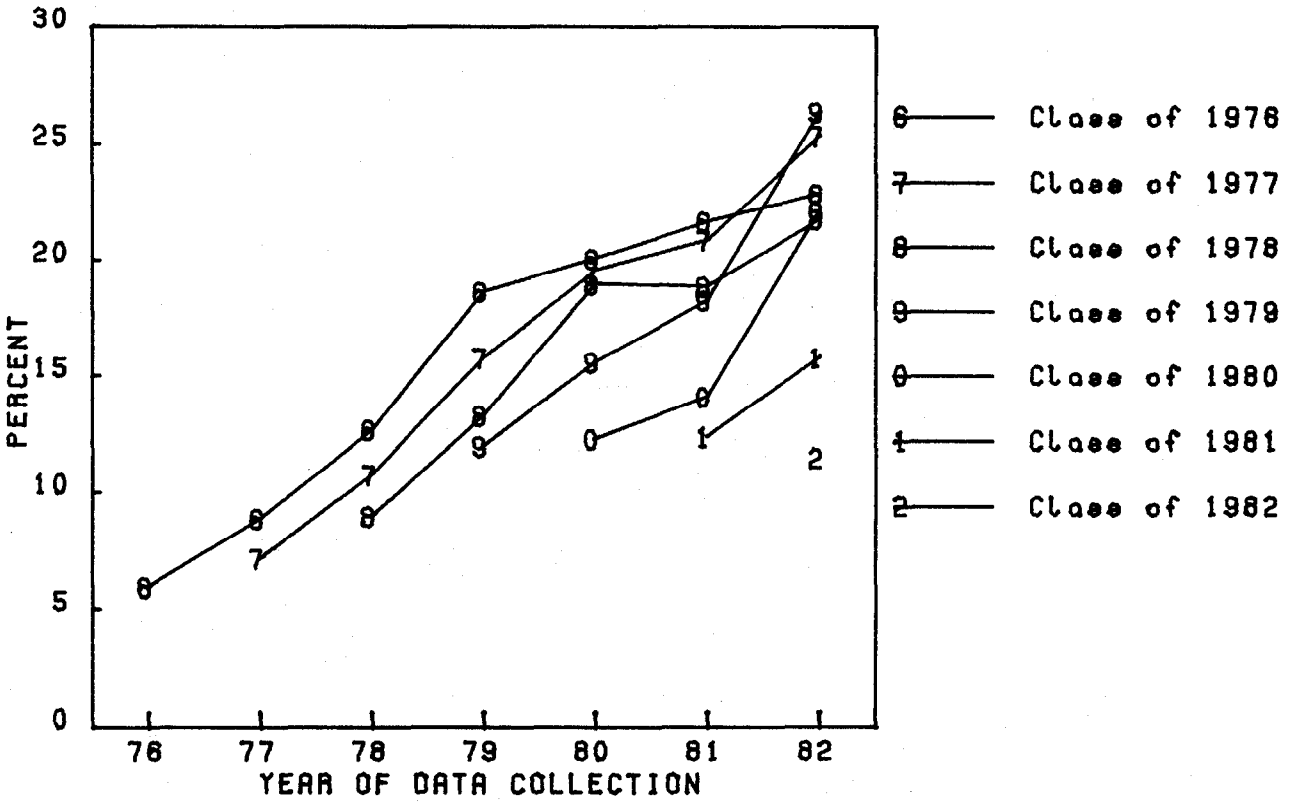

Figure 11

Amphetamine: Annual Prevalence

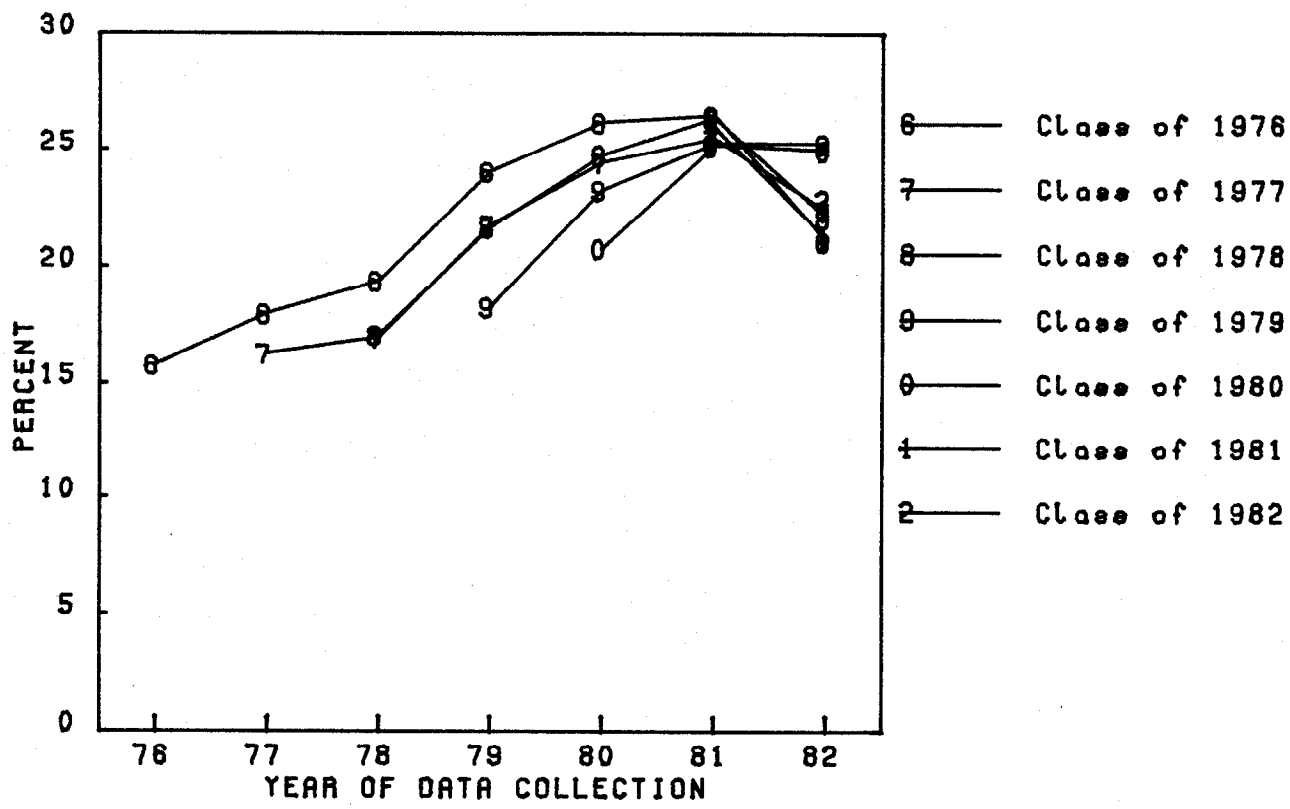

Figure 12

Methaqualone: Annual Prevalence

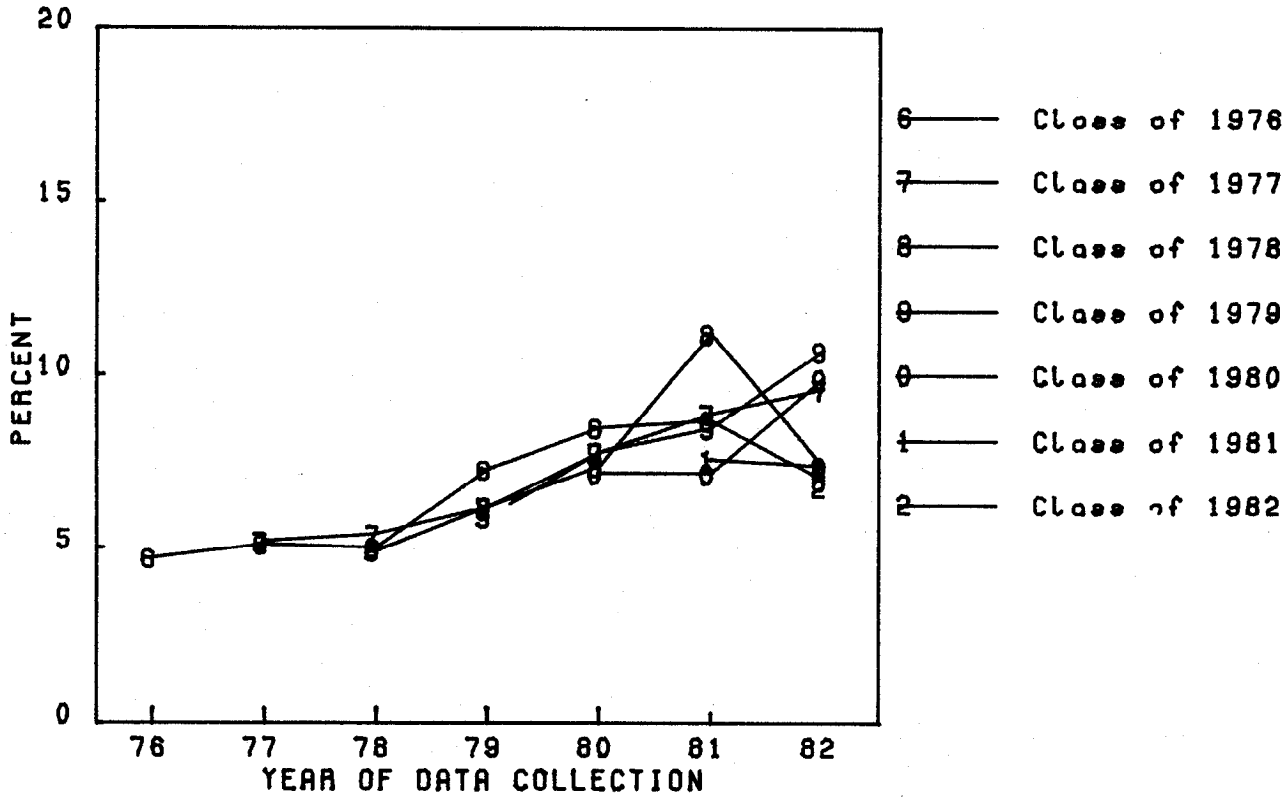

Figure 13

Barbiturate: Annual Prevalence

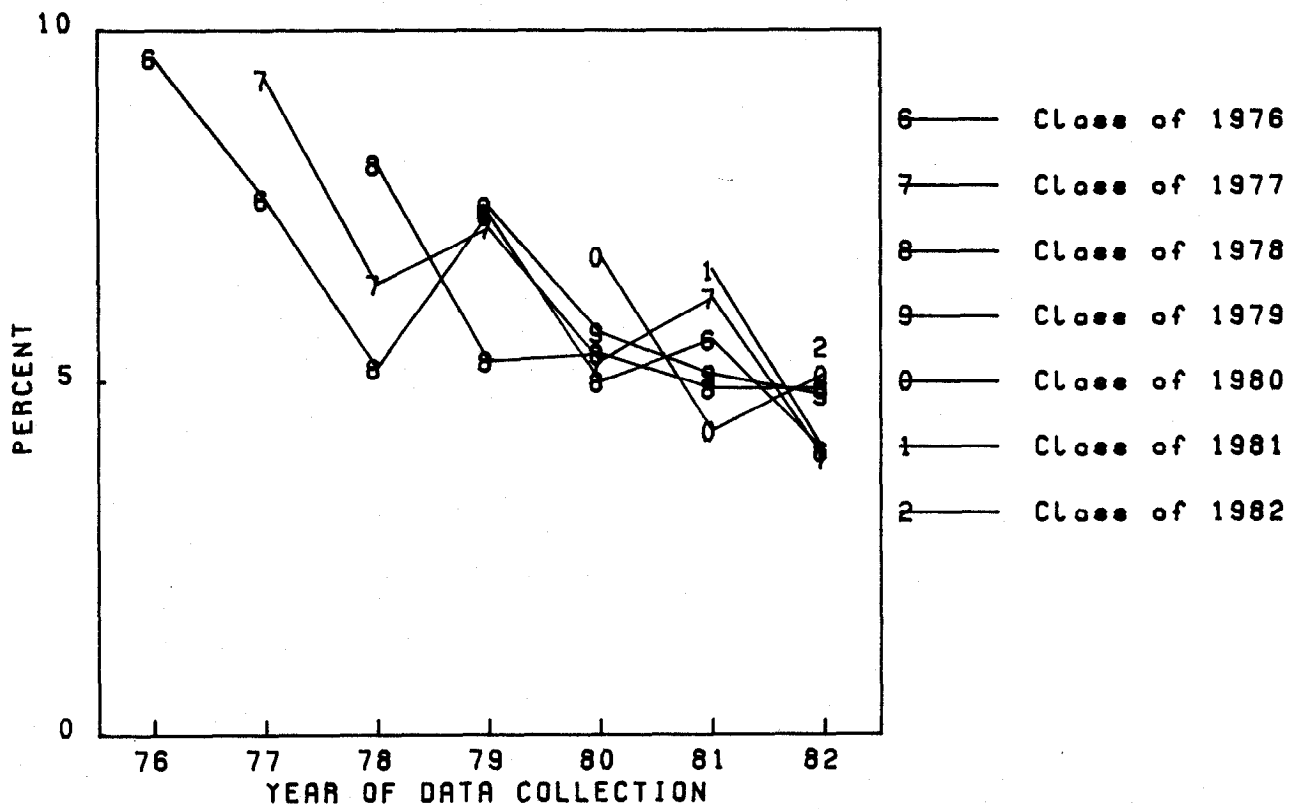

Figure 14

LSD: Annual Prevalence

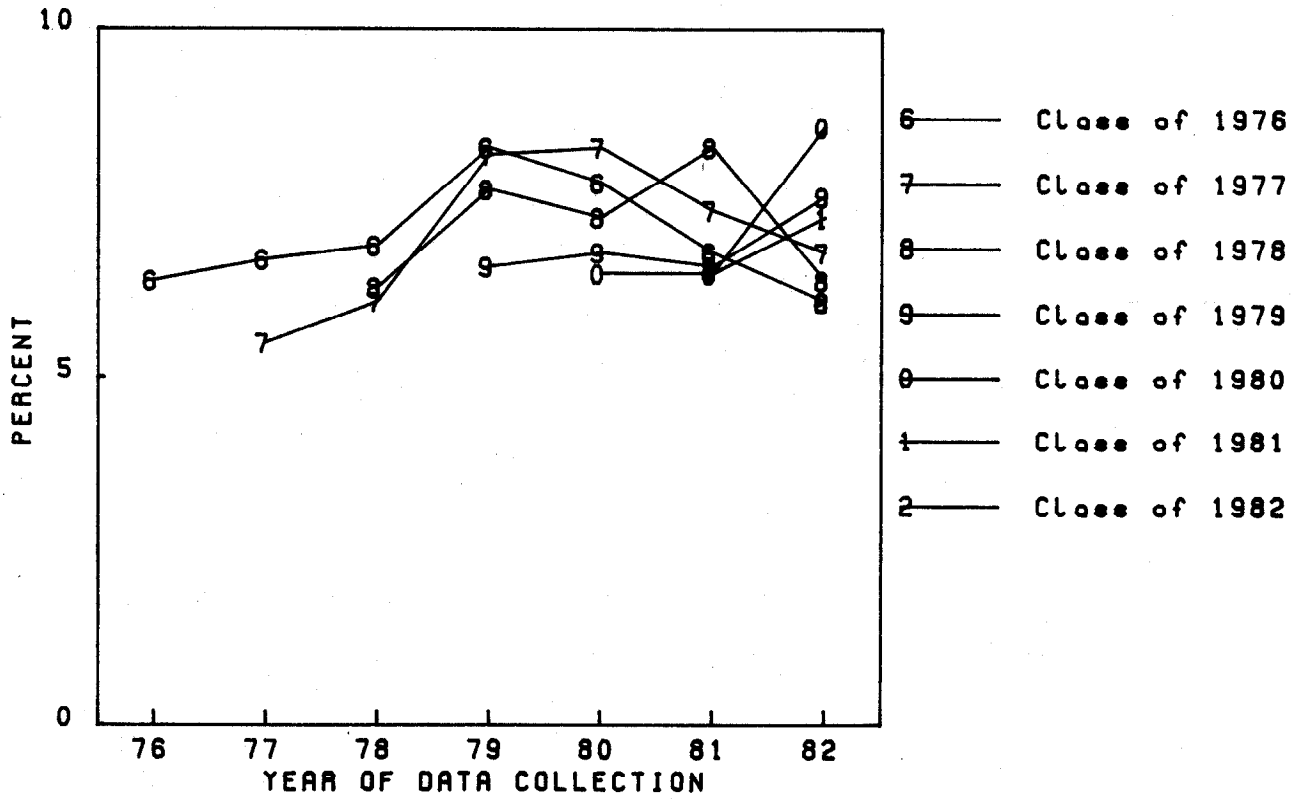

Figure 15

Psychedelics: Annual Prevalence

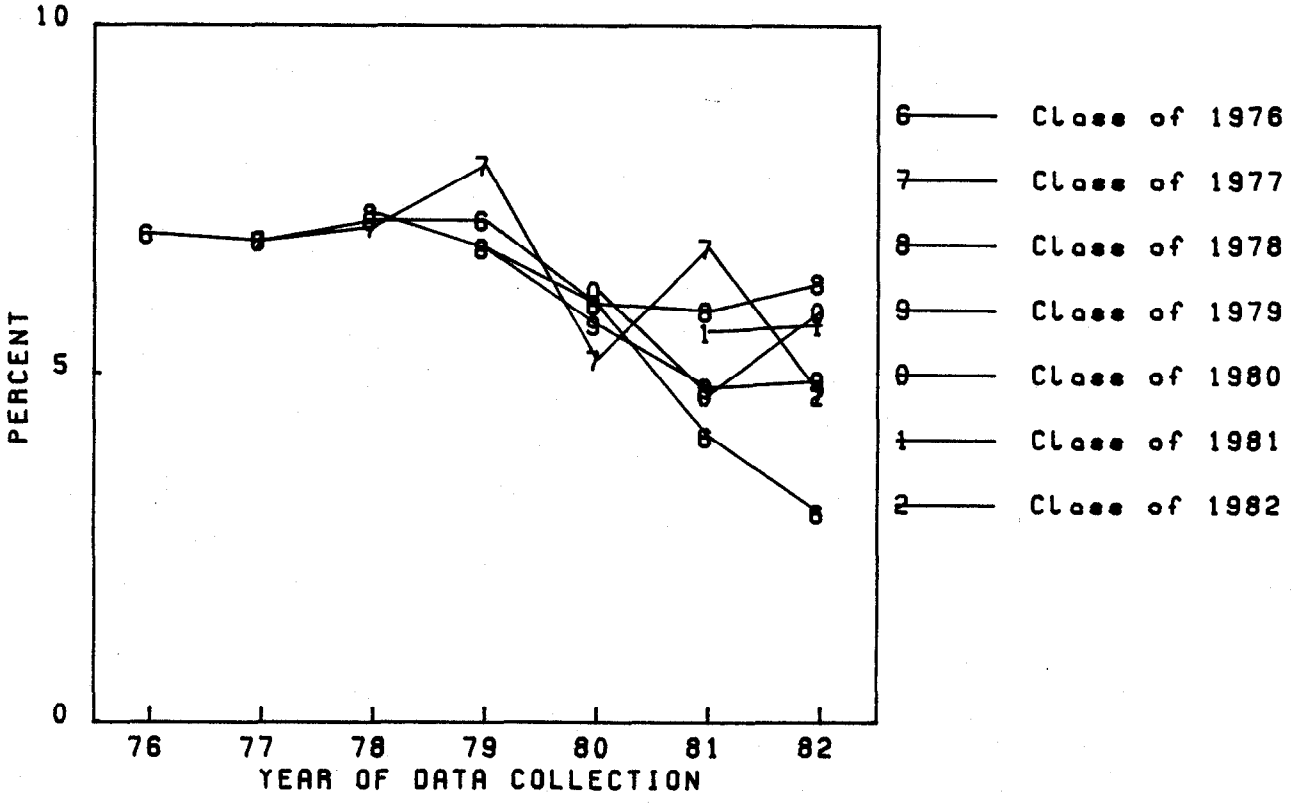

Figure 16

Tranquilizer: Annual Prevalence

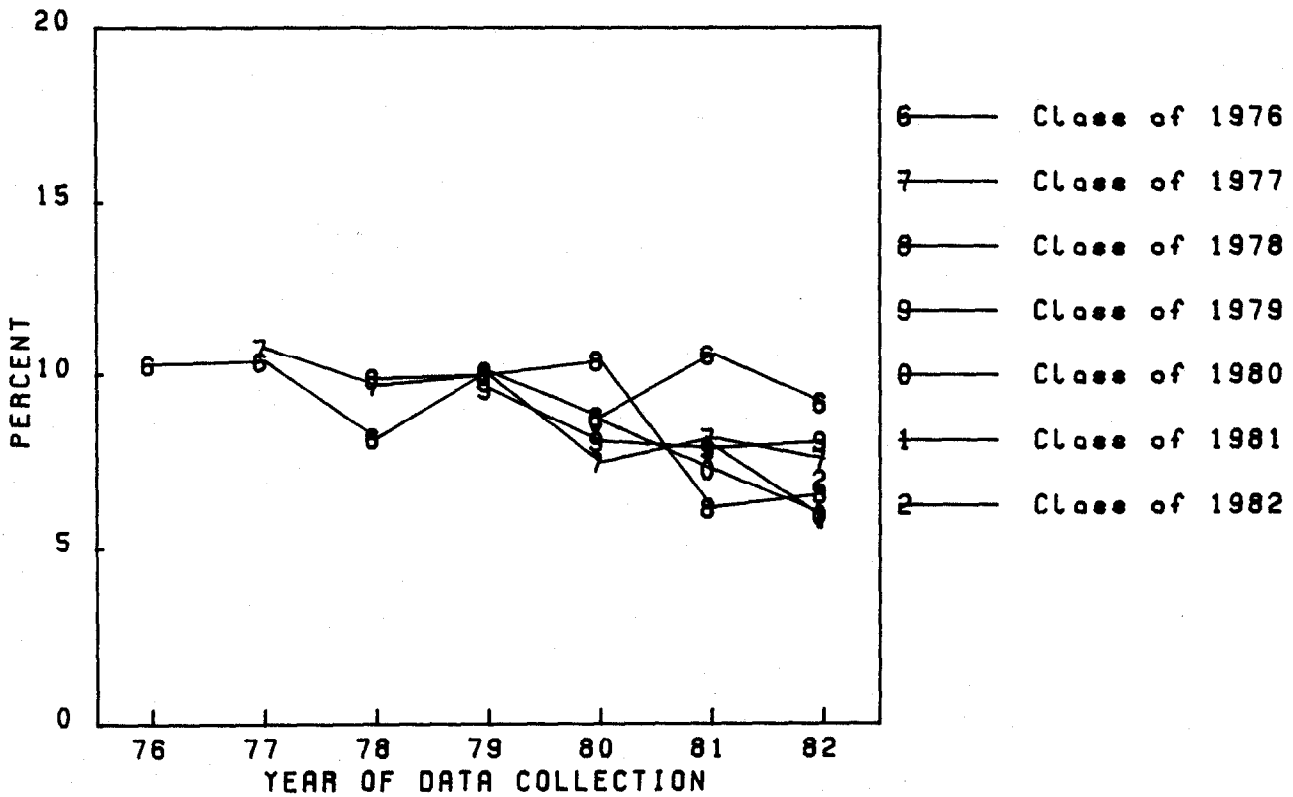

Figure 17

Heroin: Annual Prevalence

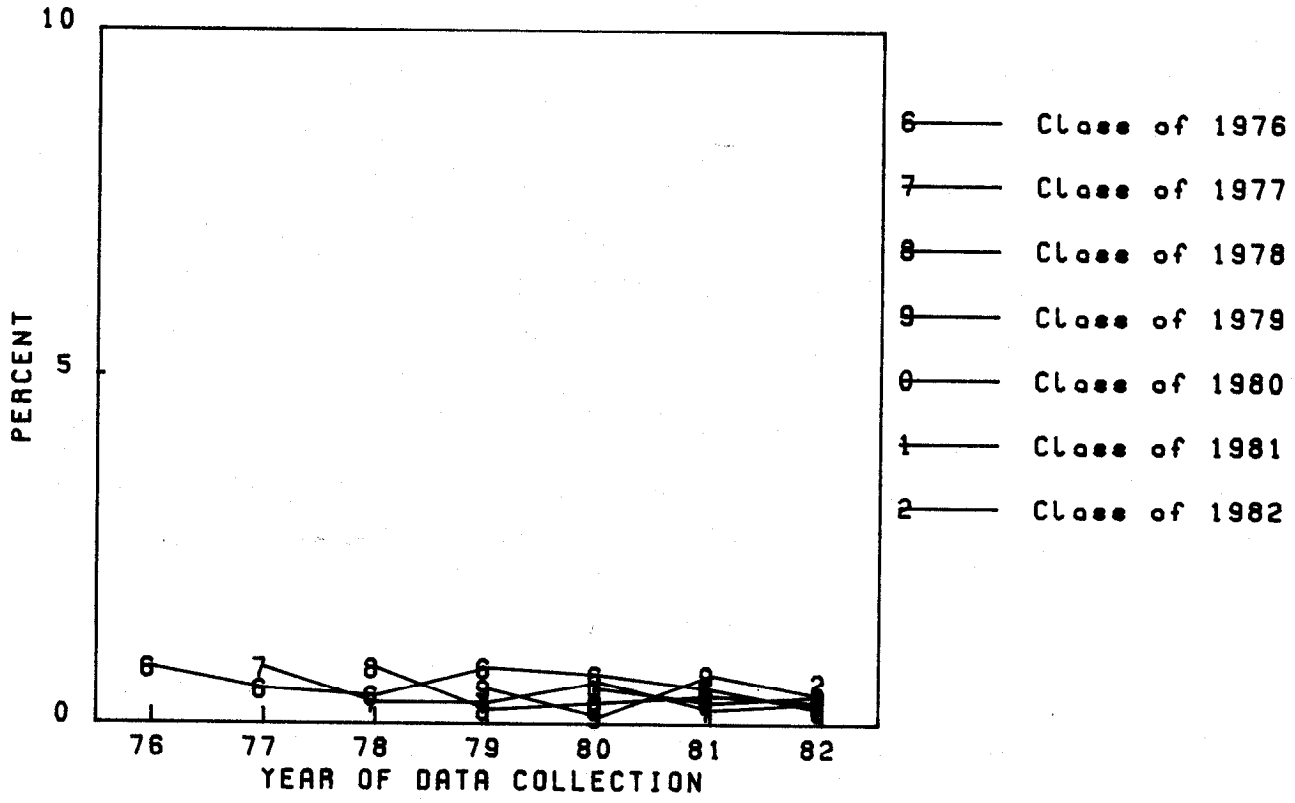

Figure 18

Narcotics: Annual Prevalence