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DOES DRUG USE LOWER WAGES?

ANDREW M. GILL and ROBERT J. MICHAELS*

This study, using microdata from the 1980 and 1984 waves of the National Longitudinal Survey of Youth, examines the effects of drug use on wages and employment. Contrary to most previous researchers' findings that illegal drug use negatively affects earnings, this analysis suggests that, once an allowance is made for self-selection effects (that is, unobservable factors simultaneously affecting wages and the decision to use drugs), drug users actually received higher wages than non–drug users. A similar analysis of employment effects shows that the sample of all drug users (which included users of "hard" and "soft" drugs) had lower employment levels than non–drug users, but the smaller sample consisting only of users of hard drugs, surprisingly, did not.

THE use of illegal drugs is predominantly an activity of young adults,[1] whose average earnings are lower than those of older persons. It is also a widespread activity. In a 1988 survey by the National Institute on Drug Abuse (NIDA), 58.9% of respondents aged 18–25 reported that they had at some time in their lives used an illegal drug, and 32.0% said they had done so in the past year.[2] Drug use also differs among occupations and by employment status. According to a 1985 NIDA survey, 15.7% of technical and sales personnel aged 18–34 were currently using marijuana, compared to 27.6% of production and craft workers. Of the unemployed in that age group, 29.9% were current users, a higher percentage than in any occupation listed. (Voss 1989:36, 40, 43.)

With one exception, previous studies have found that drug use lowers wages or earnings. We believe those studies are fundamentally flawed because they do not deal with the determinants of the decision to use drugs. That decision depends on both measured and unmeasured individual attributes that may also affect earnings directly. By analogy with other studies of earnings, we must account for the possible self-selection of users. If individuals with certain characteristics are more likely than others to choose drug use, cross-sectional OLS estimates of the marginal effect of drug use on wages will be biased and inconsistent.

An accurate estimate of the drugs-earnings relationship is important for public policy. A finding of a negative

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The parameter estimates in this study were obtained using LIMDEP, Version 5, executed on a VAX. Copies of the computer programs used to generate the results presented in this paper are available from Andrew Gill at the Department of Economics, California State University, Fullerton, CA 92634.

[1] U.S., National Institute on Drug Abuse (NIDA) (1989), p. 17.

[2] U.S., NIDA (1989), p. 17. The corresponding figures for 26–34-year-olds are 64.2% ever used and 22.6% used in the past year. Additional information from this survey is summarized in Gill and Michaels (1991).

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effect might be used to rationalize a policy of enforcement against users, who, it might be argued, do not realize the consequences of their choices. If drug use does not affect earnings but is instead undesirable because of externalities such as crime, admonishing rational persons to "just say no" for selfish reasons will likely be ineffectual. If drug use neither adversely affects earnings nor gives rise to negative externalities, the rationale for any restrictive policy at all is weakened.

We estimate the effect of drug use on wages using the 1980 and 1984 samples of the National Longitudinal Survey of Youth (NLS-Y). In 1984, respondents were between 18 and 27 years old. They were queried extensively about drug use, and for our purposes the responses are known to be sufficiently truthful (see below). After summarizing prior studies, we outline a bivariate selectivity model that allows us to decompose the difference between the wages of users and nonusers into three factors: the effects of differences in observable productivity and personal characteristics of the two groups, the effects of differences in regression coefficients for these characteristics, and the effects of self-selection.

Previous Findings on Substance Use and Earnings

Illegal Drugs

Despite its policy importance, the drug-earnings relationship has seldom been studied. Harwood et al. (1984:A-19–A-24) used NIDA survey data to examine the effects of use of a number of drugs. They estimated the logarithm of household income as a linear function of independent variables that included a dummy variable with a value of one if the respondent had ever in the past used marijuana daily for a month or more. Other independent variables included some that are common in earnings equations (Mincer 1974), such as education, race, occupational category, and marital status. Data limitations forced the authors to exclude others, such as measures of health status, urban residence, union status, and work experience.

Since Harwood et al. only presented regression coefficients on marijuana use, it is difficult to comment further on their results (1984, Table A-8). The R^2 and F statistics for their regressions, in comparison with those we present below, are strikingly low. Their measure of drug abuse seems quite arbitrary,[3] as does their choice of which results to present. Although they ran a wider set of regressions (Harwood et al. 1984: A-20), they only reported the effects of marijuana use on three measures of household income.[4] Their estimates of its negative effect ranged from 27.9% to 40%, depending on the labor force characteristics of the subsample used in the estimation. Based on an estimate of the marijuana-using population, they then estimated an aggregate productivity loss of $25.7 billion in 1980. Oddly, they found no significant effect of hard drug use on income, despite an intuition that if marijuana has such a strongly negative effect, hard drugs should be even more detrimental.[5]

[3] In three of the equations shown, they included two measures of "Current Use" among the independent variables (Harwood et al. 1984, Table A-7). There is no indication of why two measures of the same thing should be included in the same regression, or how these measures differ. In any case, five out of the six coefficients of the "Current Use" variables are insignificant, and the one significant coefficient indicates that higher current use raises the household income of employed persons. Harwood et al. do not comment on this result.

[4] The available data, from a NIDA survey, did not include income for the individual user. Harwood et al.'s three income measures were household incomes of all persons in the sample, household incomes of those in the labor force, and household incomes of those who were employed. The authors explain the absence of other results by stating that "the variables and their coefficients are not printed here only to keep the presentation clear" (1984:A-22). The same reason may explain why they do not separately present the results for the various gender and marital status subsamples. There are large and well-documented differences in drug consumption by gender and marital status (Voss 1989:39).

[5] Their explanation for the lack of significant results is twofold. First, "heavy drug users *may* have life styles that make them unlikely to be captured in household surveys" (p. A-20; emphasis ours). Second, the "prevalence of drug use other than marijuana is much lower than that for marijuana." The first of these is conjecture. Regarding the

Harwood et al.'s regressions do not address our principal concerns. Might there be simultaneity between labor market participation and drug use, and might there be unobservable factors that simultaneously affect wages and the decision to use drugs? If, for example, drug users are individuals who are naturally prone to idleness, any inferences from uncorrected regressions are, at best, suspect.[6]

In another study, French et al. (1990) examined the effects of various drug abuse treatment approaches on employment and earnings. Using data from the 1979–81 Treatment Outcome Prospective Study (TOPS), they found that measures of annual, weekly, and hourly earnings of those admitted to federally funded treatment centers increased by 16%, 6%, and 8%, respectively, between the year prior to admission and the year after discharge.

Although their work is valuable for understanding some of the effects of treatment, French et al., like Harwood et al., did not address the question of self-selection. In the TOPS sample, average weekly earnings of those who were working either full- or part-time prior to treatment ($208) were lower than for the general population ($235). The authors did not analyze the determinants of this difference, which may reflect the self-selection of lower earners into drug use. Similarly, the percentage of the treatment sample employed either full- or part-time at the time of admission (31%) was lower than the corresponding figure for the general population (64%). Both the employment and earnings differences may be due to the fact that only those drug users with problems acute enough to warrant treatment were in the TOPS sample.

Kaestner (1991) is the only study known to us that explicitly accounts for the self-selection of drug users. In one section of his paper, Kaestner investigates the effect of nonzero lifetime cocaine and marijuana use on wages and reports wage differentials favoring drug users. Using data from the 1984 NLS-Y, he finds, for example, that among men aged 18–27, users of drugs would be expected to have a 17%–19% higher wage than nonusers (p. 400).

Although these results are broadly similar to those we report below, our study differs from Kaestner's in several respects. First, his definition of drug user differs from ours. Second, his switching regression does not analyze the potential bias due to self-selected labor force status, because he finds this factor insignificant in prior regressions. (Our analysis finds it important.) Third, the two studies differ in their findings on the implied returns to users' and nonusers' characteristics. Finally, we investigate how drug use affects employment, and Kaestner does not.

The Importance of Self-Selection: Evidence from Studies of Alcohol

Most studies of the alcohol-earnings (or alcohol-productivity) relationship have also failed to account for the endogeneity of an individual's choice of whether or not to use alcohol. Another section of Harwood et al.'s study summarized nine different prior estimates of the effects of alcohol use on productivity or income (1984, Table A-5). All of the cited studies found negative effects, ranging from 14% to 30%. To our knowledge, none of these studies dealt with the self-selection problem.

In their own study, Harwood et al. analyzed microdata from a 1979 survey by the National Institute of Alcohol Abuse and Alcoholism (NIAAA) using regres-

second, 12.5% of 1984 NLS-Y subjects reported the use of harder drugs in the previous year.

[6] Sociologists have analyzed panel data on drug use and the workplace, but have yet to study the drug-earnings relationship. For example, Mensch and Kandel (1988) attempted to determine whether certain job conditions were associated with drug use as reported to the NLS-Y. Their multiple regressions to explain drug use included job characteristics (insecurity, discretion, and so on) and a variety of demographic independent variables. They did not include any measures of income or earnings, and did not correct for the possible self-selection of drug users into jobs with the characteristics investigated. Other researchers are investigating biological (primarily genetic) characteristics that might influence the likelihood of drug abuse (Pickens and Svikis 1988).

sions similar to those they performed for illegal drugs. They found that problem drinkers (by their definition) lived in households with incomes 21% lower than those of non-problem drinkers.[7] Using methods similar to ours, Heien and Pittman (1989) reanalyzed the NIAAA data. They found that "problem drinker" status was, in fact, endogenous, and after accounting for this endogeneity, drinking had no significant effect on family income.

The other available alcohol study that accounts for self-selection is Berger and Leigh (1988). Using data from the 1972–73 Quality of Employment Survey, Berger and Leigh estimated wage equations using the same basic method as Heien and Pittman. As in Heien and Pittman's data, unadjusted mean wages were higher for drinkers than for nondrinkers (12.8% for men and 25.2% for women). Log-wage regressions corrected for selectivity bias yielded *larger* differences in wages for both genders. Berger and Leigh also found that the percentage difference between drinkers' and nondrinkers' wages became greater as the frequency of drinking increased, peaking at two times per day.[8]

Method and Data

The Model

Selectivity bias arises if unobservable factors affecting the drug use decision are correlated with unobservable factors affecting wages. If such a relationship exists, estimates of the effect of drugs taken from regressions for the user and nonuser populations will be biased. Put simply, the wages of users and nonusers will not be observed randomly.[9]

Our study contains two potential sources of selectivity bias: first, the drug use decision may be endogenous; and second, employment status may be endogenous. The latter source of bias, which has been explored extensively in the human capital literature (see Reimers 1983), comes into play when unobservable factors in the employment outcome are correlated with unobservable factors in the wage equation. In this study, the situation is further complicated by the fact that drug use itself may affect the likelihood of employment.

A bivariate selectivity model can account for these sources of bias. Let I_1 be an unobserved variable denoting the utility difference between the two states of using drugs and not using drugs, and let I_2 be an unobserved index denoting the likelihood of employment. We assume that I_1 and I_2 are linear functions of human capital and personal characteristics:

$$I_1 = \mathbf{Z_1 b_1} + u_1 \tag{1}$$

$$I_2 = \mathbf{Z_2 b_2} + u_2. \tag{2}$$

Equation (1) is a reduced-form threshold equation determining drug use. We are assuming that the drug use decision depends in part on the wage differential, if any, associated with drugs. Thus, the vector Z_1 includes both exogenous variables that are determinants of earnings and personal attributes that are only determinative of drug use. Equation (2) is a reduced form for the employment outcome. Z_2 also includes factors influencing the drug use decision, since it is expected that drug use affects the probability of employment. These reduced-form equations are used to calculate probabilities and selectivity terms. Their disturbances are assumed to be normally distributed with mean zero.

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[7] The unadjusted mean income of alcohol abusers in the survey was, in fact, 15.6% higher than that of non-abusers, a statistically significant difference (Heien and Pittman 1989:573).

[8] At that level of consumption, Berger and Leigh's sample size was too small to support any strong inferences. At least for moderate drinking, their findings are consistent with the medical literature, which has frequently found that moderate drinking is associated with improved health. See references in Berger and Leigh (1988).

[9] Numerous other studies of earnings deal with such endogeneity. For example, see Lee (1978), Duncan and Leigh (1980, 1985), and, more recently, Idson and Feaster (1990).

Wage equations for drug users and nonusers complete the model:

$$\text{(3)} \qquad \ln W_D = \boldsymbol{X_D g_D} + e_D$$

$$\text{(4)} \qquad \ln W_{ND} = \boldsymbol{X_{ND} g_{ND}} + e_{ND}$$

In (3) and (4) the log of an individual's wages is a linear function of a vector of human capital and personal characteristics, a form developed by Becker (1975) and Mincer (1974). Their error terms e_D and e_{ND} are assumed to be normally distributed with means of zero.

As noted, the estimation of (3) and (4) is complicated by self-selection in both the drug-use decision and the employment outcome. Let $i = 1, 2 \ldots, N$ index individual observations. The expected value of the log wage in each activity is given by

$$\text{(5)} \qquad \mathrm{E}(\ln W_D) = \boldsymbol{X_D g_D} + \mathrm{E}(e_D \,|i \ni Y_1)$$

$$\text{(6)} \qquad \mathrm{E}(\ln W_{ND}) = \boldsymbol{X_{ND} g_{ND}} + \mathrm{E}(e_{ND} \,|i \ni Y_2),$$

where

$$\text{(7)} \qquad Y_1 = \{i \mid I_1 > 0, I_2 > 0\}$$
$$Y_2 = \{i \mid I_1 < 0, I_2 > 0\}$$

As suggested, if unobserved factors affecting wages are correlated with the drug choice and employment outcome, estimating separate wage equations for users and nonusers who are employed will produce biased estimates. Obtaining consistent estimates requires that instruments be found for the conditional error terms in (5) and (6). The selection criterion in this study is based on a model of joint decisions in which both outcomes are observed, as described in a different context by Maddala (1983:282) and Fishe et al. (1981). That is, we observe the drug use decision and the employment outcome for the entire sample. The appropriate selection correction thus depends on whether the errors in equations (1) and (2) are independent. Preliminary bivariate probit regressions for one definition of drug use, HDRUGS (see Table 1), indicated that the hypothesis $\mathrm{Cov}(u_1, u_2) = 0$ could not be rejected.[10] In this situation, the selectivity terms are simple extensions of those proposed by Heckman (1979) and Lee (1978). For example, define $a_1 = \mathrm{Cov}(u_1, e_D)$ and $a_2 = \mathrm{Cov}(u_2, e_D)$. The selection correction for the drug-use wage equation is

$$\text{(8)} \qquad \mathrm{E}\,(e_D|I_1 > 0, I_2 > 0) = a_1[\phi(\boldsymbol{Z_1 b_1})/\Phi(\boldsymbol{Z_1 b_1})] + a_2[\phi(\boldsymbol{Z_2 b_2})/\Phi(\boldsymbol{Z_2 b_2})],$$

where Φ is the cumulative distribution function of a standard normal variable and ϕ is its density.

Estimates of b_1 and b_2 are obtained by the probit method. They are used to construct selectivity terms, which are appended to the wage equations. The wage equations that account for self-selection are then given by

$$\text{(9)} \qquad \ln W_D = \boldsymbol{X_D g_D} + a_1\lambda_1 + a_2\lambda_2 + v_D$$

$$\text{(10)} \qquad \ln W_{ND} = \boldsymbol{X_{ND} g_{ND}} + a_3\lambda_3 + a_4\lambda_4 + v_{ND},$$

Where the λ's are the selectivity terms and the a's their coefficients.

The Data

There are several reasons to believe that well-designed surveys can and do provide useful estimates of the true prevalence of drug use. Checks on the consistency of answers within and between surveys can be made, and such a check shows that there is broad agreement between NIDA and NLS-Y figures. Drug abuse reporting also provides some unique opportunities

[10] The estimate for $\mathrm{Cov}(u_1, u_2)$ was 0.0007, t = 0.023. The parameter estimates from the bivariate probit analysis did not differ from those estimated independently, nor did the signs and significance levels for the selectivity terms and the other wage-equation variables. For the other definition of drug use, DRUGS, the maximum likelihood estimator for the bivariate probit run would not converge. The LIMDEP program terminated, indicating arithmetic faults. We were unable to rectify this problem, and thus we estimated the parameters for the drug choice and employment outcome by independent probit equations. It is not clear how this problem affects the final estimates in this case.

for reliability checks. In various studies, responses by individuals have been compared with police records, medical records, and reports of friends. Researchers have generally concluded that such studies point up the basic usefulness of the survey data for establishing trends and demographic differences in use patterns. (Rouse, Kozel, and Richards 1985.)

Our data are from the 1980 and 1984 waves of the NLS-Y, for persons 18 to 27 years old in 1984. Regarding the reliability of self-reported drug use in the NLS-Y, Mensch and Kandel (1988) compared individual responses in earlier surveys to those in later surveys. They also compared the distributions of NLS-Y responses to the distributions of responses by a similar population in a contemporaneous survey that was taken anonymously and without interviewers. Their broad finding was an under-reporting of drug use other than marijuana in later years of the NLS-Y. This under-reporting, however, was concentrated among individuals who claimed to have been only experimental users in early surveys and who either forgot or lied about those experiments in later surveys. Since it seems fair to assume that drug use affects earnings only to the extent that it is more than experimental, this bias is probably unimportant.

We present definitions of our variables in Table 1. We analyze two definitions of drug use, both of which apply to the year prior to a subject's 1984 interview. The first, DRUGS, is defined as a yes response to any questions about use for virtually all illegal drugs, including barbiturates, amphetamines, and marijuana. The second, HDRUGS, is restricted to yes responses to questions about so-called hard drugs such as cocaine, heroin, and psychedelics.[11]

No obvious inferences can be made from simple cross-tabulations.[12] 38.2% of the sample (2388/6240) reported using some illegal drug during the past year, and 12.6% reported using a "hard" drug. Differences in labor force status between users and nonusers are not extreme: 78.9% of users were employed, with the remainder either unemployed or not in the labor force; 80.7% of hard drug users were employed; and 82.3% of the remaining sample were employed. Drugs had been used in the past year by 37.3% of the employed and by 42.5% of those not employed. Popular impressions of differences in the use of drugs by race are also either erroneous or exaggerated, judging by these data: 39.5% of white respondents to the NLS-Y, but only 33.9% of nonwhite respondents, reported illegal drug use over the prior year. The difference for hard drugs is more striking: 13.9% of whites reported using them, but only 8.1% of nonwhites.[13]

Other descriptive NLS-Y statistics appear in Table 2. They are given by drug use activity (DRUGS) and by employment status. As shown, mean wages are higher for users. A lower proportion of users are married, and a higher proportion of them are male. Although their differences in educational attainment are small, the proportion of nonusers exceeds than that of users in professional, administrative, and service occupations. Table 2 also presents some measures of personal attributes that may influence drug use. Mean measures of drinking behavior (KPDRINK and BARMO) differ substantially between users and nonusers, as do indicators of prior illegal activity (ILLACT and ILLINC). Drug users report being less satisfied with their current jobs (JOBSAT).

[11] "Hard drug" is neither an economic nor a pharmacological term. The only obvious distinction between hard and soft drugs is that legal penalties applicable to the former are frequently more stringent than those applicable to the latter. The evidence that hard drugs are in some sense more damaging to users or more addictive is elusive.

[12] These tabulations are available on request from the authors.

[13] A similar pattern of use by different races has persisted to the present, despite a substantial change in the mix of drugs consumed. See NIDA (1989: 106–13).

Table 1. Variable Definitions.

Variable	*Definition*
DRUGS	= 1 if respondent used any of the following drugs in the past year (without physician approval): amphetamines or stimulants, barbiturates or sedatives, cocaine, heroin, inhalants, psychedelics, tranquilizers, other drugs, other narcotics, marijuana.
HDRUGS	Includes only cocaine, heroin, inhalants, psychedelics, other drugs, and other narcotics.
WAGE	Hourly wage.
EDUC	Years of schooling.
EXPER	Proxy for years of labor market experience: (AGE − EDUC − 5).
INCSPOUS	Income of spouse.
FATHED	Years of schooling—father.
MOTHED	Years of schooling—mother.
DEPENDENTS	Number of dependents, excluding spouse.
VTR	= 1 if respondent received any vocational training in 1979, 1980, 1981, or 1982.
UNION	= 1 if job is covered by a union contract.
GOV	= 1 if government job.
HEALTH	= 1 if the respondent reports that health problems limit the kind of work he or she can do.
MARRIED	= 1 if married and spouse present.
MALE	= 1 if male.
WHITE	= 1 if white.
RURAL	= 1 if lives in a rural area.
NE	= 1 if residence is in the Northeast.
NC	= 1 if residence is in the North Central region.
SOUTH	= 1 if residence is in the South.
PROF	= 1 if occupation is professional, managerial, or technical.
SALES	= 1 if occupation is sales.
ADMIN	= 1 if occupation is administrative support/clerical.
SERVICE	= 1 if occupation is service.
CRAFT	= 1 if occupation is precision production, craft, or repair.
FFF	= 1 if occupation is farming, forestry, or fishing.
MANUF	= 1 if industry is manufacturing.
RETAIL	= 1 if industry is retail.
PROFESS	= 1 if industry is professional and related services.
ESTEEM	= 1 if respondent disagreed or strongly disagreed with the following statement: I have a positive attitude toward myself (1980).
JOBSAT	= 1 if respondent reported disliking his or her job somewhat or very much.
ILLACT	= 1 if respondent was ever charged with breaking a law (excluding minor traffic offenses) (1980).
ILLINC	= 1 if respondent reported receiving any income or support from illegal activities (1980).
KPDRINK	= 1 if respondent answered yes to the following question: During the past year have you sometimes kept on drinking after promising yourself not to?
BARMO	Frequency of going to bars in month prior to interview.
λ_1	Selectivity term for drug choice (users).
λ_2	Selectivity term for employment outcome (users).
λ_3	Selectivity term for drug choice (nonusers).
λ_4	Selectivity term for employment outcome (nonusers).

Results

The Effects of Drug Use on Wages

Table 3 presents coefficients for the wage regressions. Drug use is defined by HDRUGS in the left two columns, and by DRUGS in the right two.[14] The coefficients of the human capital variables are consistent with those found in other wage studies. Returns to education, experience, and vocational training are lower for drug users than for nonusers. Similarly, returns to these variables are lower for users of hard drugs than for users in the more general category of DRUGS. If drug use

[14] The reduced-form drug use and employment equations on which the selectivity terms in Table 3 are based are available from the authors on request. For those individuals not employed, occupation, industry, and union status were defined for the most recent job.

Table 2. Descriptive Statistics by Employment Status and Drug Use Category: 18–27-Year-Old Respondents to the 1980 and 1984 Waves of the National Longitudinal Survey of Youth. (Standard Deviations in Parentheses)

	Employed		*Not Employed*	
Variable	*Nonuse*	*Use*	*Nonuse*	*Use*
WAGE	5.88 (3.18)	6.05 (3.04)	—	—
EDUC	12.86 (2.03)	12.75 (1.88)	12.48 (1.96)	12.20 (1.97)
EXPER	5.09 (2.68)	5.16 (2.18)	4.61 (2.91)	4.94 (2.71)
VTR	0.23	0.23	0.19	0.17
UNION	0.17	0.17	—	—
GOV	0.13	0.09	—	—
MALE	0.47	0.61	0.44	0.57
WHITE	0.78	0.82	0.69	0.75
MARRIED	0.37	0.24	0.31	0.19
HEALTH	0.03	0.03	0.06	0.04
DEPENDENTS	0.40 (0.79)	0.31 (0.71)	0.44 (0.87)	0.31 (0.73)
INCSPOU	3822.67 (7525.47)	2131.30 (5827.60)	2930.82 (6971.05)	1537.99 (5196.79)
FATHED	11.06 (3.92)	11.83 (3.54)	10.71 (4.16)	11.57 (3.88)
MOTHED	11.10 (3.14)	11.63 (2.77)	10.82 (3.50)	11.51 (2.93)
RURAL	0.16	0.11	0.15	0.09
NE	0.18	0.21	0.17	0.18
NC	0.26	0.23	0.27	0.29
SOUTH	0.39	0.33	0.38	0.29
PROF	0.20	0.17	—	—
SALES	0.10	0.11	—	—
ADMIN	0.23	0.18	—	—
SERVICE	0.20	0.18	—	—
CRAFT	0.10	0.14	—	—
FFF	0.03	0.02	—	—
MANUF	0.20	0.21	—	—
RETAIL	0.20	0.22	—	—
PROFESS	0.21	0.13	—	—
ESTEEM	0.05	0.04	0.08	0.06
JOBSAT	0.10	0.14	—	—
ILLACT	0.06	0.16	0.05	0.21
ILLINC	0.09	0.27	0.11	0.28
KPDRINK	0.03	0.11	0.03	0.10
BARMO	0.84 (1.17)	1.57 (1.34)	0.64 (1.06)	1.43 (1.35)
λ_1	—	0.87	—	—
λ_2	—	0.32	—	—
λ_3	−0.53	—	—	—
λ_4	0.31	—	—	—
Observations	3170	1883	682	505

does result in lower returns to human capital characteristics, it seems intuitively reasonable to expect the use of harder drugs to yield larger negative effects. On the contrary, however, there are large differences in intercepts that favor drug

Table 3. Log Wage Regression Results: Adjusted Coefficients by Drug Use Category and Drug Use Definition.[a]
(Standard Errors in Parentheses)

	HDRUGS		DRUGS	
Variable[a]	*Nonuse*	*Use*[b]	*Nonuse*	*Use*[b]
EDUC	0.0695**	0.0341**	0.0745**	0.0469**
	(0.0068)	(0.0152)	(0.0081)	(0.0094)
EXPER	0.0375**	0.0268**	0.0407**	0.0297**
	(0.0480)	(0.0108)	(0.0056)	(0.0065)
VTR	0.0555**	−0.0534	0.0631**	0.0185
	(0.0186)	(0.0441)	(0.0219)	(0.0065)
MARRIED	0.0499**	0.0326	0.0539**	0.0347
	(0.0192)	(0.0524)	(0.0215)	(0.0292)
RURAL	−0.1084**	−0.0254	−0.1085**	−0.0681*
	(0.0229)	(0.0692)	(0.0261)	(0.0376)
GOV	−0.0402	−0.0427	−0.0456	−0.0587
	(0.0256)	(0.0727)	(0.0291)	(0.0428)
HEALTH	−0.1187**	0.1539*	−0.1464**	0.0332
	(0.0465)	(0.0919)	(0.0517)	(0.0653)
UNION	0.1798**	0.2372**	0.1822**	0.2283**
	(0.0220)	(0.0505)	(0.0260)	(0.0315)
WHITE	0.0248	−0.1129*	0.0084	0.0222
	(0.0221)	(0.0604)	(0.0253)	(0.0328)
MALE	0.1508**	0.0459	0.1942**	0.0732**
	(0.0176)	(0.0417)	(0.0209)	(0.0261)
SOUTH	−0.1096**	−0.1099**	−0.0939**	−0.1153**
	(0.0218)	(0.0471)	(0.0262)	(0.0309)
NC	−0.1056**	−0.1816**	−0.0955**	−0.1175
	(0.0213)	(0.0556)	(0.0271)	(0.0325)
NE	−0.0337	−0.0337	−0.0126	−0.0486
	(0.0233)	(0.0525)	(0.0295)	(0.0334)
λ_1	—	−0.1373**	—	−0.0486
		(0.0525)		(0.0373)
λ_2	—	−0.6807**	—	−0.6391**
		(0.2232)		(0.1425)
λ_3	−0.0288	—	−0.0221	—
	(0.0591)		(0.0295)	
λ_4	−0.3748**	—	−0.2116	—
	(0.1141)		(0.1376)	
Constant	0.6471**	1.6808**	0.4373**	1.1561**
	(0.1448)	(0.3919)	(0.1774)	(0.2344)
Adj. R^2	0.2498	0.2286	0.2441	0.1964
F-Stat.	59.66	7.38	42.31	18.93
N	4,325	623	3,170	1,883

[a] Also included in the regressions are controls for occupation and industry. In the interest of space, they are excluded from the table.
[b] The standard errors reported in this column are the uncorrected OLS standard errors.
* Statistically significant at the .10 level; ** at the .05 level (two-tailed tests).

users in general, and especially users of hard drugs. Below, we show that intercept differences dominate differences in returns to characteristics, yielding predicted wage differentials that favor drug users.

The coefficients of the selectivity variables show the importance of controlling for self-selection. For HDRUGS, there is negative selection (negative truncation) in the wage distribution for users, evidenced by the fact that the mean of the selectivity variable for users, λ_1, is positive whereas its coefficient is significantly negative. The estimated wage in drug use, conditional on the drug choice, is lower than the unconditional estimate (Idson and Feaster 1990:110). This result implies that the average wage actually observed for drug users is lower than it would be if drug use were a random phenomenon.

The coefficient of λ_1 provides an estimate of the covariance between the disturbances in the drug use and wage equations. As one possible explanation of our results, assume that an unobserved characteristic leading to drug use is an individual's genetic predisposition to idleness.[15] Individuals with that characteristic will be relatively unproductive, regardless of whether they choose to use drugs. Thus, for a given set of observed characteristics, including drug use, they will earn lower wages. The negative selectivity (the negative coefficient times the positive mean of λ_1) implies that a randomized experiment will yield a lower average wage for nonusers and a higher average wage for users, as compared with the observed sorting. Random sorting would put more of these less motivated individuals into the non-use category. In the equation for nonusers, λ_3 carries an insignificant coefficient. Thus, there is no evidence of selection bias in the nonuser wage equation.

The coefficients of the employment selectivity terms, λ_2 and λ_4, are negative and significant for both users and nonusers of hard drugs. They are more difficult to interpret than the drug use selectivity coefficients, because the reduced-form estimates do not allow us to separate the influences of demand and supply on employment status. If supply-side factors (labor force participation decisions) predominate, the negative selectivity coefficients suggest that individuals with higher values of time in uses other than employment are less likely to be in the sample (Blau and Beller 1988:519). This explanation may be reasonable given the relative youth of the sample.

[15] This notion is purely hypothetical. We know of no evidence that any such characteristic exists.

For DRUGS, there is no evidence of selection bias due to the drug use choice. The coefficients for λ_1 and λ_3 are insignificant. The more inclusive the definition of drug use, the less important is self-selection into the activity. Continuing with the assumption that a predisposition to idleness is the relevant unobserved characteristic, it is not surprising that the observed sorting yields no significant bias. Whereas hard drug use may attract the less motivated, drug use more broadly defined may be associated with greater variation in this characteristic. A higher proportion of the more motivated individuals will be categorized as users under the broad definition.

We next decompose the raw logarithmic wage differential between the two states along the lines suggested by Blinder (1973) and Oaxaca (1973):

$$(11)\quad \ln W_{ND} - \ln W_D = X_D(g_{ND} - g_D) + g_{ND}(X_{ND} - X_D) + \lambda_D(a_{ND} - a_D) + a_{ND}(\lambda_{ND} - \lambda_D).$$

All variables are measured at their mean values. Equation (11) decomposes the raw differential into three components. In sequence, they are: (1) that attributable to differences between coefficients in the user and nonuser wage equations, including intercepts; (2) that attributable to differences in the characteristics of users and nonusers; and (3) that attributable to selection bias, the sum of the final two terms.

Table 4 presents the results of this decomposition. The first column is for HDRUGS, and the second for DRUGS. For HDRUGS, the raw logarithmic wage differential in favor of drug users is approximately 10%, shown as a negative number in the table. The logarithmic wage differential attributable to differences in the regression coefficients (excluding the selectivity coefficients) between the equations is 0.343 in favor of drug users. It can be further decomposed into a part that is explained, due to differences in returns to wage-determining characteristics, and a part that is unexplained, due to differences in intercepts. As mentioned in our

Table 4. Decomposition of Raw Wage Differential.

Description	HDRUGS	DRUGS
Raw Wage Differential: ($\ln W_{ND} - \ln W_D$)	−.10396	−0.04294
Differences Due to Coefficients Net of Selection Bias	−0.34276	−0.20764
Differences in Returns to Characteristics	0.69098	0.51116
Unexplained	−1.03374	−0.71880
Differences Due to Characteristics Net of Selection Bias	−0.05624	−0.02819
Total Selection Bias	0.29504	0.19289
Selection Bias: Drug Use	0.19946	0.05387
Selection Bias: Employment	0.09558	0.13902

discussion of Table 3, nonusers receive higher returns to their characteristics, but these returns are swamped by a large unexplained differential in favor of users. The differential in favor of drug users due to intercept differences is 1.033, whereas that in favor of nonusers due to differences in returns to characteristics is 0.690. Net of selection bias, differences in wage-determining characteristics favor drug users but contribute relatively little to the overall wage differential.

The effects of characteristics and returns to characteristics are analogous for DRUGS. Users earn approximately 4% more than nonusers. Considering only differences due to the regression coefficients, excluding selectivity terms, the estimated differential increases to approximately 20%. As before, nonusers enjoy higher returns to wage-determining characteristics, but this advantage is offset by a large unexplained differential in favor of drug users due to differences in intercepts. The differential due to intercept differences in favor of drug users is 0.719, whereas the differential due to differences in returns to characteristics in favor of nonusers is 0.511. Again, differences in mean values of the wage-determining characteristics favor drug users.

The sum of the third and fourth terms in (11) is the effect of selectivity bias. The consequences of selection bias due to the choice of drug use are striking in the case of HDRUGS. Its effect on the differential (0.199) favors nonusers, in contrast to the opposite effects of characteristics and intercepts. The same holds for the portion of the differential due to self-selection in employment. The results for DRUGS also show selection bias favoring nonusers, but the drug use effects are smaller and employment effects larger than for HDRUGS. The results for DRUGS must be viewed in light of the fact that three of the four selectivity coefficients are insignificant.

The positive effect of the drug choice selectivity bias in the wage decomposition for HDRUGS results from negative truncation in the wage distribution for drug users accompanied by positive truncation in the wage distribution for nonusers. Thus, selection bias taken by itself increases the wage gap to favor nonusers. The same is true for the effects of the employment selectivity. Its effects are also positive, because the negative selectivity related to the employment outcome is more pronounced for users.

Our results warrant comparison with those found by Berger and Leigh (1988) for the wage differential between drinkers and nondrinkers. As noted above, their estimated differential in favor of drinkers increased after adjusting for selection bias. Their estimates were approximately 34% for randomly chosen women and 45% for randomly chosen men. Our estimated differentials in favor of drug users are 29% for HDRUGS and 19% for DRUGS.[16] Moreover, when Berger and Leigh's Mills ratio estimates (Table 2, p. 1347) are combined with their equations (6) and (7), the consequences of selection bias are the

[16] Percentage differentials are calculated as $e^d - 1$, where d is the log difference given in the second row of Table 4.

same as in our study. Their wage distribution for drinkers is negatively truncated, and that for nondrinkers is positively truncated. Our finding of stronger wage effects for harder drugs may also be analogous to Berger and Leigh's tentative finding that the percentage wage differential is greatest for those who admit heavy (twice-a-day) consumption of alcohol. Among other possibilities, people may be using alcohol or drugs to "treat" themselves as alternatives to prescription drugs.

Employment Effects

To assess the impact of drug use on the employment outcome, we first perform a probit estimation of a reduced-form drug use equation. We then estimate the effect of drug use on the employment outcome by inserting the fitted values of the probability of drug use into a structural equation for employment. The results of this estimation appear in Table 5. In the drug use equations, drinking behavior and past participation in illegal activities are strongly related to drug use. The coefficients of BARMO, KPDRINK, ILLACT, and ILLINC are positive and significant for DRUGS and HDRUGS. Whites and men are more likely than nonwhites and women to be users of hard drugs, but the coefficient of WHITE is significant only for DRUGS. Those living in the South and in rural areas are less likely to use hard drugs.

In the employment equations, most coefficients have the expected signs and are significant; for example, men and the more educated are more likely to be employed. For HDRUGS, the coefficient of drug use is insignificant. In other words, users of hard drugs are no less likely than nonusers to be employed, controlling for other determinants of the employment outcome. By contrast, DRUGS is associated with a reduced probability of employment.

Our model does not allow us to make inferences about the mechanism by which drug use negatively influences employment outcomes. On the demand side of the labor market, drug use may signal low productivity, increased absenteeism, or higher insurance bills to a potential employer.[17] On the supply side, it might be complementary with leisure. If either explanation were obviously true, we would expect that the coefficient of HDRUGS would be more strongly negative than that of DRUGS, contrary to our findings. The reasons for the disparity in employment effects remain unclear.

Summary and Conclusions

Most previous studies have found that drug use negatively affects wages. We have found that accounting for selection bias results in dramatically different findings: namely, a positive relationship between wages and the use of illegal drugs, and a particularly strong positive relationship between wages and the use of "hard" drugs. Most previous studies have implicitly treated drug use as exogenous, and therefore have attributed any observed difference in wages between users and nonusers solely to the effects of drug use. We incorporate the decision to use drugs explicitly into the estimation of the wage functions. Intuitively, it seems likely that those who choose to use illegal drugs will, on average, differ from those who do not, and our results are consistent with that intuition.

To estimate the effect of drug use on earnings, we have used standard wage decomposition techniques. Some criticisms that have been leveled at these techniques in studies of discrimination (Blau and Ferber 1987) may also apply to our work. First, because of data limitations, our measure of the wage differential may be in error. One source of possible bias is our inability to account for all of the determinants of wages. Second, our relatively small sample of hard drug users limits our ability to provide reliable analyses of wages by race and gender.

[17] If drug use is a signal, however, its effects should be fairly obvious, or some more efficient signal will supplant it. The paradox of employee drug testing is that much of it takes place only because there is no reliable way of determining from observed work performance that an employee is using drugs.

Table 5. Probit Estimates of Drug Use and Employment Equations.[a] (Asymptotic Standard Errors in Parentheses)

	HDRUGS		DRUGS	
Variable	*Reduced-Form Drug Use Equation*	*Employment Equation*	*Reduced-Form Drug Use Equation*	*Employment Equation*
ESTDRUGS	—	−0.0625 (0.1469)	—	−0.1196** (0.0464)
BARMO	0.1839** (0.0171)	—	0.2149** (0.0141)	—
KPDRINK	0.2788** (0.0809)	—	0.5208** (0.0736)	—
ILLINC	0.5541** (0.0541)	—	0.5565** (0.0472)	—
ILLACT	0.3439** (0.0669)	—	0.5046** (0.0598)	—
EDUC	−0.0202 (0.0142)	0.0462** (0.0112)	−0.0419** (0.0109)	0.0435** (0.0114)
MALE	0.1332** (0.0479)	0.0838** (0.0391)	0.1085** (0.0364)	0.1116** (0.0398)
SOUTH	−0.0889* (0.0497)	0.0726** (0.0407)	−0.0131 (0.0372)	0.0662 (0.0405)
MARRIED	−0..4586** (0.0779)	0.0637 (0.0594)	−0.2204** (0.0551)	0.0405 (0.0597)
HEALTH	0.1026 (0.1159)	−0.2889** (0.0939)	−0.0667 (0.0929)	−0.2857** (0.0934)
WHITE	0.1881** (0.0626)	0.1894** (0.0458)	0.0313 (0.0448)	0.2156** (0.0459)
RURAL	−0.3037** (0.0779)	0.0815 (0.0568)	−0.2284** (0.0524)	0.0666 (0.0571)
UNION	−0.0164 (0.0626)	—	−0.0179 (0.0475)	—
ESTEEM	−0.0297 (0.1081)	−0.0671** (0.0231)	−0.0663 (0.0807)	−0.0602** (0.0227)
VTR	0.0798 (0.0529)	0.1032** (0.0469)	0.0124 (0.0413)	0.0988** (0.0465)
AGE	0.0368** (0.0111)	0.0814** (0.0092)	0.0181** (0.0085)	0.0817** (0.0091)
GOV	−0.2392** (0.0803)	—	−0.2104** (0.0574)	—
FATHED	0.0248** (0.0101)	−0.0004E-02 (0.0066)	0.0207** (0.0061)	0.0003 (0.0062)
MOTHED	0.0272** (0.0101)	−0.0056 (0.0081)	0.0227** (0.0075)	−0.0038** (0.0081)
DEPENDENTS	−0.0081 (0.0358)	−0.0601** (0.0272)	−0.0074 (0.0256)	−0.0599** (0.0271)
INCSPOUS	0.008E-03* (0.004E-03)	0.002E-03 (0.003E-03)	−0.002E-03 (0.003E-03)	0.002E-03 (0.003E-03)
Constant	−2.8389** (0.0271)	−1.7145** (0.0286)	−1.0505** (0.2069)	−1.6939** (0.2175)
χ^2	660.40	214.71	1063.0	223.52

[a] Also included are the controls for industry and occupations. In the interest of space, they are excluded from the table.
* Statistically significant at the .10 level; ** at the .05 level (two-tailed tests).

We emphasize that the above results are insufficient in themselves to support any policy recommendations. First, our measure of drug use is limited to a simple yes or no response to a question about a wide variety of drugs. Drug use, on the other hand, is a complex subject. Drugs are different from one another, as are drug users. Blacks, whites, and Hispanics use different drugs in different ways.

Second, our sample contains only persons between 18 and 27 years old. Any wage advantage to young drug users may be offset by shorter life spans or lower rates of wage growth. Such a pattern, in fact, is consistent with data in Table 3, which show that the returns to such human capital characteristics as work experience are lower for users than for nonusers. Since users have flatter wage profiles, the negative effects on earnings will not be realized until later in life. If that is true, a full life-cycle model may be appropriate.

In any case, our results are sufficiently at variance with conventional wisdom that they should be checked against other regression formulations and other samples. As they stand, however, they indicate substantial wage advantages to drug users, net of selectivity bias, on either definition of drug use. Because the unobservable factors that lead to drug use also lead to lower wages, selection bias increases the apparent wage differential between nonusers and users.

The question of whether illegal drug use is a rational choice is separable from the question of whether an individual can rationally choose a career of addiction. Those drugs that are illegal are defined as such by the vagaries of the law. An economist would be hard pressed to defend treating the choice of marijuana use as rational when it is legal (as it was prior to the 1930s) and irrational when it is illegal but penalties are low. Addiction may likewise be a rational choice, particularly for activities or substances that the individual views as benign (Becker and Murphy 1988; Michaels 1988). Relatively few of those who sample illegal drugs become habitual users, and drug use effectively ceases for all types of user by age 35 (Gill and Michaels 1991:96). Whether the individual properly considers the possible long-term risks of drug use is an empirical question, made more complex by uncertainty about the nature of those risks. Regarding tobacco, Viscusi has found that "both smokers and nonsmokers greatly overestimate the lung cancer risk of cigarette smoking, and . . . [t]hese risk perceptions in turn significantly reduce the probability of smoking" (1990: 1253).[18]

Our findings pose some important questions regarding the generally accepted view of "drug abuse." Does drug use raise productivity and hence wages, at least in the short run? If the answer is yes, how can these results be rationalized? Economists should be among the professionals who can most easily address such questions. As one possible economic story, assume that individuals are rational consumers of both legal and illegal drugs. In the same way that they take aspirin to deal with headaches, they take alcohol or other substances to deal with attitudinal and emotional difficulties. If so, then illegal drug use might improve productivity in the same way that legal drug use does. As is the case for legal drugs, some persons may misdiagnose their problems or take incorrect doses of inappropriate substances.

Regarding policy, our findings cannot justify an endorsement of legalization, particularly if the returns to human capital characteristics are lower for users, as Table 3 suggests. Beyond that consideration, drug use might create such detrimental externalities (similar to, for

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[18] Official views are quite to the contrary. According to the President's Office of National Drug Control Policy, "individuals who experiment with drugs make poor assessments of their own vulnerability. And once they start using drugs regularly, their opinions about their own powers of resistance become even more suspect. No one is a good judge of his own case, and drug users are the worst judges of their own addiction" (1990:5). This emphatic assertion follows a discussion in which the authors acknowledge that there is currently no way of identifying biological or personality factors that might predispose a person to addiction.

example, drunk driving) that welfare is maximized by continuing to discourage self-medication. Legalization for adults might be supportable, and legalization for younger persons might not be. In 1915, the American Medical Association editorialized in its journal that opium was the most valuable single drug then available (Szasz 1975:72). Today, doctors are severely constrained in their ability to prescribe it, and persons who choose to prescribe it for themselves risk legal penalties, poisoning, and overdoses. The choice of self-prescription, however, may not be irrational in light of our findings.

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