Repeated Measures Estimation of Measurement Bias for Self-Reported Drug Use With Applications to the National Household Survey on Drug Abuse

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ABSTRACT

Direct estimates of response bias for self-reports of drug use in surveys require that essentially error free determinations of drug use be obtained for a subsample of survey respondents. The difficulty of obtaining determinations which are accurate enough for estimating validity is well-documented in the literature. Methods such as specimen (e.g., hair, urine) analysis, proxy reports, and the use of highly private and anonymous modes of interview all have to contend with error rates which may only be marginally lower than those of the parent survey. Thus, any methodology for direct validity estimation must rely to some extent on approximations and questionable assumptions.

In this chapter, the authors consider a number of methods that rely solely on repeated measures data to assess response bias. Since the assumptions associated with these approaches do not require highly accurate second determinations they may be more easily satisfied in practice. One such method for bias estimation for dichotomous variables that is considered in some detail provides estimates of misclassification probabilities in the initial measurement without requiring that the second measure be accurate or even better than the first. This methodology does require, however, that two subpopulations exist which have different rates of prevalence but whose probabilities of false positive and false negative error are the same.

The applicability of these methods for self-reported drug use are described and illustrated using data from the National Household Survey on Drug Abuse. In the discussion of the results, the importance of these methods for assessing the validity of self-reported drug use are examined.

INTRODUCTION

The self-report is an integral component of the research methodology for measuring the prevalence of substance abuse and other stigmatized behaviors. While a growing body of literature supports the validity of the self-report, there are also studies that question its validity (see Mieczkowski (1991) for a review of validation research in this area). These studies suggest that response validity for drug use is highly dependent upon the construction of questions, procedures for administration, the investigator's perceived intentions, and the respondent's cognitive fitness. Given the importance of monitoring drug use prevalence, trends, and risk factors for the U.S. population, considerable research has been conducted to improve the validity of the self-report for sensitive topics; examples include the use of more private and/or anonymous reporting methods and attempting to motivate honest reporting by incentives or personal appeals (for example, see chapters by Lessler and O'Reilly, and Tourangeau, this volume).

To compare the accuracy of alternative data-collection methodologies for obtaining self-reports, some information on the reporting error associated with the measurement processes is required. If the objective of a methodological study is to estimate the magnitude of measurement bias, then error-free determinations of drug use are typically required for a sample of study subjects. For other methodological studies, it may only be necessary to obtain determinations that have better measurement error properties than the methodologies being evaluated. If no criterion data are available for estimating measurement bias, it is sometimes sufficient to know the direction of the reporting bias in order to select the best data-collection method. As an example, in many cases it is reasonable to assume that stigmatized behaviors will generally be underreported by the study population. In such cases, the data-collection methodology that produces the highest prevalence rate is deemed the most valid method (see Biemer 1988 for a critique of this approach).

As the preceding discussion affirms, measurement error evaluation methodology is critical for the improvement of the survey design and survey methods. In addition, evaluation methods are used to assess the components of total error in reported estimates from drug use prevalence studies, and these data help define the limitations of the survey results for policy decisions and other uses of the data.

Nonetheless, all methods for estimating validity, reliability, and response bias are themselves subject to questions of validity.

This chapter focuses on a number of methods for assessing the validity of self-reports of drug use. In particular, the discussion is confined to methods for estimating measurement bias that rely on repeated measurements of the same characteristics for the same individuals. Examples are reinterview methods, test-retest, record check studies, and biological test validation methods. In the next section, a number of meaurement error indicators and measures are reviewed that have been used in the literature to describe the measurement accuracy and precision of survey data. In the discussion of reliability and bias estimation, several approaches for estimating these measurement error indicators using repeated measurements methods are presented. Using a general, two-measurement model for measurement error, each estimation approach is seen as a design for restricting the parameter space of the overspecified general model by setting some parameters to zero and/or others to the same, unknown constant. These restrictions then impose requirements on the evaluation designs that must be met in order for the model assumptions to hold.

A substantial part of the chapter presents the results of an evaluation of a recently developed statistical method for estimating false positive and false negative reports from repeated measurement studies. The method was developed by Hui and Walter (1980) for the evaluation of medical diagnostic testing procedures. Sinclair and Gastwirth (1993) applied the method for the evaluation of survey measurements and extended the methodology in ways that enhance the method's applicability for survey evaluation. The method provides estimates of misclassification probabilities in the initial measurement without requiring that the second measurement be without error or even more accurate than the first measure. The methodology does require, however, that two domains can be defined that have different rates of prevalence but have identical probabilities of misclassification.

For this application, the method is applied to data from the National Household Survey on Drug Abuse (NHSDA) to estimate the misclassification errors associated with self-reports of alcohol, marijuana, and cocaine use. False negative and false positive probabilities (and their standard errors) by various demographic subgroups and geographic areas are presented in the section discussing the application of the Hui-Walter method to NHSDA data.

Finally, the last section summarizes the results of the application of repeated measurement methods for the evaluation of self-reports of drug use and presents conclusions regarding their application to NHSDA data.

REVIEW OF MEASUREMENT ERROR TERMINOLOGY

In this section, several measurement error concepts relevant to the study of self-reported drug use are reviewed. The study is restricted to the error in a single dichotomous response variable, denoted by *y*, because this type of response is quite often encountered in drug use measurement. As an example, *y* may denote a "yes or no" response regarding the use of specific drugs during some period or it may denote a response to a category of use in a multiple category response set. Let *y* denote the measurement for some characteristic associated with the *i*-th survey respondent where $y_i = 1$ if the respondent possesses the characteristic and $y_i = 0$ if otherwise. Let $_i$ denote the corresponding true value for the respondent. Following Cochran (1968), the following misclassification probabilities are defined:

(1)

where and are referred to as the probability of a false negative and the probability of a false positive, respectively. Thus, the expected value of given is
(2)

Measurement Bias

Let , the true prevalence of the characteristic in the target population; let , the expected observed prevalence. Let the measurement bias of the measure *y* be defined as . Thus, from (2)

(3)
From (3), it can be seen that the measurement bias is 0 or small relative to " if either:

Condition (a) implies that there is almost no chance for a misclassification error. Condition (b) implies that the expected number of false positive errors in the population approximately equals the expected number of false negative errors. As Cochran (1968) points out, this latter condition is quite unlikely in most applications, so that zero measurement bias is usually an indication that condition (a) holds.

Note that for drugs with low prevalence rates such as cocaine and heroin, " will be many times smaller than (1 - "), and a relatively small false positive rate can have large consequences on the bias. As an example, suppose " = 0.010, = 0.30, and . = 0.010. Then, " = (0.010) (0.30) = 0.0030 while (1 - ") . = 0.99 x 0.010 = 0.0099. Thus, the contribution to bias due to false positives is 3.30 times larger than the contribution due to false negatives, although the probability of a false negative is 30 times greater than the probability of a false positive. Using equation (3), $B(y) = 0.0030 + 0.0099 = 0.0069$, the relative bias, defined by $RB(y) = B(y)/"$, is 0.0069/0.010 = 0.69; that is, estimates of " based on *y* will be 69 percent larger, on average, than ". Thus, for rare drugs, the consequences of even a small false positive rate can be substantial.

Measurement bias is important in survey work because it is directly related to the bias in estimators of means, proportions, and totals. Let $p = \%y_i/n$ denote the sample proportion for a simple random sample. Then the bias in *p* for estimating ", the true population proportion, is defined as which is also given by (3).

Reliability

Roughly speaking, reliability refers to the degree of consistency of responses from independent, replicated measurements of the same characteristic. The statistical definition of the reliability ratio, *R*, is the proportion of the variance that is *not* measurement variance, where *measurement variance* is defined as ; that is, the average variance within respondents and between hypothetical, independently replicated measurements. Thus, *R* can be expressed mathematically as

(4)

Biemer and Stokes (1991) show that, for dichotomous responses, *R* can be quite difficult to interpret because it is a complex function of the misclassification probabilities and ". They show that under the model in (2)

(5)

where *P* = "(1-)+(1-"). and *Q* = 1 - *P*. Further, they show that (a) for two domains or subpopulations having identical probabilities of misclas-sification, the reliability ratio for one domain can be substantially larger than the ratio for the other solely as a consequence of the difference in their respective prevalence rates. As an example, suppose that for domain 1, " = 0.50 while for domain 2, " = 0.10. Further, let = 0.00 and . =.10 for both domains. Then, using equation (5), *R* = 0.82 for domain 1 and *R* = 0.47 for domain 2. On this basis, it would be wrong to conclude that the responses from domain 1 are of higher quality than are those from domain 2. Thus, in this respect, *R* can be misleading as an indicator of data quality. (b) From equation (5), it can be shown that the reliability ratio can be very high although there is a large amount of misclassification error. As an example, suppose the false positive probability is zero () while the false negative rate is high, say 10 percent (). Further suppose that . This situation is often encountered in drug use measurement for rarely used drugs. Then it can be shown that *R* = 0.90, suggesting very high reliability in the measure. Further, the relative bias in the measure is -10 percent, which is nontrivial.

While good reliability is not necessarily an indicator of good data quality, poor reliability usually indicates that the measure is subject to a large measurement bias. This is especially true when the prevalence rate is small, as with cocaine or heroin use. As an example, consider the case where , , and . Here, 1 - *R* = 0.43, and the relative bias of the measure defined above is *RB(y)* = 0.38 or 38 percent. This correspondence between *I* = 1 - *R,* called the index of inconsistency, and the relative bias for small prevalence rates is not coincidental. By comparing (5) to (3) divided by ", it can be verified that *I* and *RB(y)* will be close whenever " is small. Further, when " is small, the cause of poor reliability is a high and disproportionate number of false

positives compared with the number of false negatives in the population. To illustrate, in the example, the expected number of false negatives in the population is N x 0.050 x 0.10 = 0.0050N, where N is the population size. This compares with N x 0.95 x 0.025 = 0.024N false positives— approximately 5 times as many false positives as false negatives. Thus, one may conclude that when the prevalence of the characteristic is small, poor reliability is usually an indication of a large positive bias in the estimator of the prevalence rate. By a similar argument, one can conclude that when the prevalence rate is large (say, " > 0.90), poor reliability is usually an indication of a large negative bias in the estimator due to a high false negative rate. For " between 0.10 and 0.90, poor reliability is an indication of a large expected number of false positives and/or false negatives. However, little can be said regarding the direction of the bias or whether the net effect of misclassification error results in either a small or large bias in the estimator of the prevalence rate.

To summarize, this discussion shows that in some situations the reliability ratio can be a good indicator of measurement and estimator bias. Further, a large value for the estimator of R is no assurance of good data accuracy. A low value of R is an indication of large misclassi- fication errors in the data. Finally, in some situations, R can help researchers determine whether the misclassification error problem is a result of high false negative and/or high false positive probabilities.

Validity

Bohrnstedt (1983, p. 97) states that validity is an indicator of "the degree to which an instrument measures the construct under investigation." Bohrnstedt discusses a number of alternative concepts of validity proposed in the psychometric literature for describing data quality. Some of these are predictive validity, concurrent validity, empirical validity, and theoretical validity. These concepts and others are discussed in some detail in Groves (1989). Of particular relevance to the present discussion is theoretical validity (TV) which, in terms of the model, is defined as the correlation between the observed measure and the conditional expectation of the observed measure, called the true score. Thus,

(6)

As with most concepts, theoretical validity is defined as a correlation between two constructs (i.e., measures or true scores). Because validity does not depend upon the existence of a true value, it is the preferred indicator for describing the quality of measures of psychological states, attitudes, or knowledge. Biemer and Stokes (1991) show that, under the error model proposed above for dichotomous data, , the reliability ratio. They further show that under more general models, . Thus, reliability is an upper bound on theoretical validity; consequently, a measure may be reliable but lack validity. This is similar to the result shown for measurement bias: A measure may be reliable but still be substantially biased. This result further implies that an unreliable measure cannot be valid. Note, however, that an unreliable measure may still be unbiased. For the classification error models considered here, reliability and validity, while conceptually different, are mathematically equivalent indicators. Thus, as a measure of data quality for categorical variables, the limitations of the reliability ratio are also limitations of validity measures.

It is not uncommon to find the terms "validity" and "measurement bias" used synonymously. It is important to note that these concepts are quite different. As an example, if some positive number, *C*, is added to every measurement, the validity of the measure is unchanged while bias is increased by *C*. The advantage of validity as an indicator of data quality is that, unlike measurement bias, validity does not require that true values exist for the constructs under study.

Mean Square Error

Whereas measurement bias, reliability, and validity are defined at the response level, the mean square error (MSE) is defined at the estimator level. The mean square error of an estimator is a measure of accuracy that is often used for estimators of population parameters. Let " be any estimator of ", then

(7)

the sum of the square of the bias and the variance. Suppose that is the simple expansion mean under simple random sampling, denoted by *p*. As mentioned above, the bias in *p* is *B(y)* defined in (3). Biemer and Stokes (1991) show that for small samples from large populations,

(8)

where P was defined before as $E(y_i)$. An unbiased estimator of the variance is the usual estimator,

(9)

where $q = 1 - p$. Thus, under the assumed model, the usual variance estimator is unbiased in the presence of measurement error. It will be shown subsequently that this is not true under more general models.

These variance formulas show that misclassification error can sometimes result in smaller variances for estimators of proportions and totals. Consider the situation where " = 0.5. In this situation, the variance of the sample proportion is at its maximum. Thus, misclassification can only reduce the variance. One exception to this is when the misclassification errors are correlated, as happens with interviewer error. If interviewers exert influence over the misclassification error for respondents in their assignments, then misclassification errors are correlated and equation (7), which was derived under the assumption of unit-to-unit independent misclassification error, no longer holds. Under a more appropriate model for this situation, misclassification error always results in an increase in estimator variance. Further, the usual estimators of variance may be substantially biased. Biemer and Stokes (1991) discuss models that are appropriate for the study of interviewer errors and dichotomous response variables.

ESTIMATION OF RELIABILITY AND BIAS

This section considers methods for estimating the components of error for the dichotomous measurement error model. These methods are test-retest, true value measurements, and repeated measurements. The assumptions underlying these methods will be discussed in terms of a general model for two measurements. Models for multiple measurements are essentially extensions of this basic model.

Let y_{ti} denote the t-th measurement on unit i for $t = 1,2$ and $i = 1,...,n$. In analogy to the single measurement model, the assumptions are as below.

General model assumptions:

Note that and if and only if the false negative errors and the false positive errors, respectively, corresponding to measurements 1 and 2 are independent. Under the general model, the probabilities of misclassification may differ between trials (assumptions i and ii) and further, the second trial outcomes are not independent of the first trial outcomes (assumptions iii - vi). Including ", seven parameters are associated with this model. However, only 3 degrees of freedom are available for estimation for a dichotomous variable with two measurements. Thus, as will be shown subsequently, additional assumptions are needed to estimate any of the parameters.

Test-Retest Methods

As discussed in the previous section, although the interpretation of the reliability ratio is difficult in the dichotomous case, estimates of reliability contain some information on bias that can be useful in studies of the accuracy of drug use measurement. The most common method of estimating reliability for self-reports is the test-retest method. This method includes reinterview studies as well as surveys in which replicate measures are embedded in a single interview and also reinterview studies. In reinterview studies, a subsample of the original respondents is recontacted for the purpose of obtaining a second set of measurements for the original interview characteristics.

Let $t = 1$ denote the first measurement and let $t = 2$ denote the second measurement or reinterview response. For the test-retest measurement model, the assumptions of the general model are replaced as follows.

Test-retest assumptions:

(i) Independence

(ii) Homogeneity

Assumption (i), (independence), which replaces assumptions (iii) to (vi) in the general model, essentially states that the errors in the two measurements are independent. That is, whether a false positive or false negative error is made for the second measurement does not depend upon whether an error was committed for the first measurement. For embedded replication there is a risk that respondents may simply repeat the erroneous response made on the first on the second measurement. When the second measurement is collected after some time has elapsed since the first measurement, this is less of a risk. Yet, as several researchers have shown, correlated

errors can persist even when the reinterview is conducted weeks after the initial interview (O'Muircheartaigh 1991; Bailar 1968).

Assumption (ii), (homogeneity), which replaces assumptions (i) and (ii) in the general model, states that the false positive and false negative probabilities are the same for both measurements. Thus, the aim of the design of the second measurement is to replicate the first measurement by, for example, using identical procedures, questions, or interviewer competencies. For reinterview surveys where the second measurement is obtained in a separate interview with the respondent, the reinterview design should replicate, to the extent possible, the same essential survey conditions that existed in the first interview. For replicate measures embedded with the same instrument, this assumption is more easily satisfied. Despite the potential difficulties with the test-retest assumptions, the method remains the most commonly used technique in survey methodology for estimating reliability.

To define an estimator of the reliability ratio, *R,* for dichotomous data, let *a*, *b*, *c*, and *d* denote the cell counts for the 2 x 2 measurement cross- classification table, as follows:

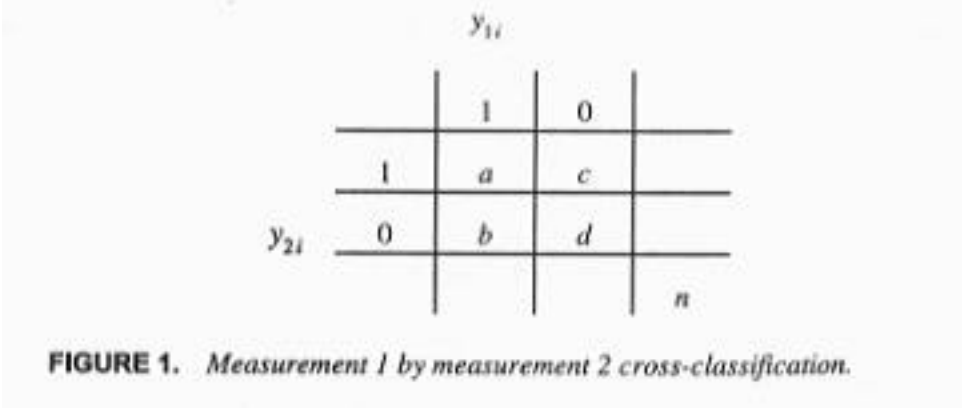

FIGURE 1. *Measurement 1 by measurement 2 cross-classification.*

Then, an estimator of *R* is where

where $q_t = 1 - p_t$, $t = 1,2$ and is an estimator of the index of inconsistency. These estimators assume that respondents are sampled using a simple random sampling design; however, for more complex sampling designs, weighted cell counts are typically used to estimate *R.*

It has been shown (Bureau of the Census 1984) that when the test-retest assumptions are not satisfied, the estimates of *R* can be

substantially biased. Violations of assumption *(i)* are usually due to errors that are positively correlated between trials. In this situation, is an overestimate of *R*. In the Bureau of the Census work (1984), it is shown that the bias in *R* is approximately $\$_T I$ where $\$_T$ is the between-trial correlation. As an example, if $R = 0.70$ and $\$_T = 0.20$, then the bias in is approximately 0.20(0.30) = 0.06 and, thus, overestimates *R* by approximately 6 percent. When assumption *(ii)* is violated, estimates a complex function of the reliabilities associated with each trial. Thus, interpretations of *R* based upon the above model can be misleading in these situations.

True Value Measurement Methods

To estimate measurement bias and the misclassification probabilities for self-reports, the traditional methodology has relied upon true value measurements. For drug use measurement, true values have been obtained from:

- administrative records, such as arrest records and drug treatment reports;

- hair, urine, and other specimen analyses to detect the presence of drugs in the specimens; and

- reinterviews using better methods than were used in the first interview, such as more private modes of interview, neutral (out-of-home) settings, and better question design.

With any of these methods, the usual modeling approach is to assume the following:

True value assumptions:

That is, it is assumed that the second measurement is the true value, or mathematically, $y_{2i} =$ $_i$. Thus, an estimator of the bias in the measurement y_1, assuming simple random samples is

(10)

If y_2 in figure 1 now denotes the true value, and using the notation for the cell counts in that table, the estimates of the false negative and false positive probabilities are respectively,

and

As before, weighted counts may be used for unequally weighted samples.

Occasionally, the assumptions for the true value model hold only approximately and a more appropriate set of assumptions is:

Improved measurement assumptions:

(i) Independence

(ii) Improved second measurement

In words, it is assumed that the second measurement is not free of error, but that the probability of error in the second measurement is smaller than that for the first measurement. Furthermore, the errors in both measurements are independent. Under these assumptions, it can be shown that if and have the same sign,

where is given by (10). Thus, the usual estimator of bias is biased downward. However, if , then may still provide a useful approximation for .

It should be noted that, under the improved measurement assumptions, the estimators and , given above for the true value model, are both biased and the directions of the biases are unknown. However, in this situation the estimation method discussed in the next

section can be used to estimate the misclassification probabilities associated with both the first and second measurements.

Repeated Measurements: The Hui-Walter Method

In some studies, two or more measurements of

are available for a sample of respondents; however, the assumptions made for test-retest and true value models are not tenable. For example, the second measurement is not perfect, nor even better than the first measurement. Neither is it plausible to assume that the second measurement is a replication of the first. Hui and Walter (1980) consider this situation in the evaluation of diagnostic tests. In this situation, the presence or absence of a disease may be indicated by two tests, each having probabilities of misclassification that are nonzero, nontrivial, and procedure dependent. Sinclair and Gastwirth (1993) applied the Hui-Walter estimation methodology for estimating the measurement error in self-reports in the evaluation of labor force characteristics in the Current Population Survey (CPS). Here the method is considered for the estimation the false positive and false negative probabilities for self-reported drug use.

Consider the case where two measurements are taken from each individual in two subpopulations or domains indexed by g. For each domain g, let A_g, B_g, C_g, and D_g denote the four cells in figure 1 as follows: A_g = cell (1,1), B_g = cell (1,0), C_g = cell (0,1), and D_g = cell (0,0).

Then the probability that a randomly selected individual from domain g is classified in each cell is as follows:

Assuming independence in the classifications between the two domains, the probability of observing for g = 1,2 is therefore

This likelihood function contains 14 parameters and only (2 x 3 =) 6 degrees of freedom for estimation. To reduce the number of parameters, Hui-Walter and Sinclair-Gastwith assume the following.

Hui-Walter independence assumptions:

(i) Independence

(ii) Homogeneity between domains:

In words, this assumption says that:

- Misclassification probabilities differ between the two measurements, but are the same for both domains (g = 1,2),
- The prevalence rates differ between domains, and
- Misclassification errors are independent between trials.

These assumptions reduce the number of parameters to six, viz., $_1$, $_2$, $._1$, $._2$, $"_1$, and $"_2$. A solution for this formulation can be obtained using maximum likelihood estimation. This model will be referred to as the Hui-Walter independence model.

The assumption of equal error rates across domains is easily justified for many diagnostic tests of the types discussed by Hui and Walter

(1980). Their example considers two tests for the detection of tuberculosis that exhibit the same error distributions across socioeconomic subgroups. In the survey setting, the misclassification errors may be highly correlated with the prevalence rates. Therefore, it is important to choose the two domains carefully to ensure proper application of these methods.

For their application to the CPS, Sinclair and Gastwirth (1993) define the two domains based on race and gender: white males and white females. Thus, it is not necessary that the two domains partition the entire population. Although the results of their study only apply to these two domains, important insights may be gleaned for the entire population by studying this part of it. Sinclair and Gastwirth demonstrate the importance of defining the two domains such that their respective prevalence rates for the characteristic of interest are markedly different. Because the characteristic of interest in their study was labor force participation, their choice of race and gender would seem appropriate, as labor force participation rates are considerably higher for white males ($"_1 = 0.75$) than for white females ($"_2 = 0.55$). Further, the assumption of equal error probabilities for the two domains is also plausible: Each domain is administered the same questions by the same interviewers using the same survey procedures. However, the assumption of independence between the errors for the two trials may not be justified. O'Muircheartaigh (1991) estimates that the between-trial correlation for labor force participation varies in the interval [0.3, 0.5] when the second measurement is obtained using a replicate reinterview survey. Sinclair and Gastwirth consider the effects of between-trial correlations on the resulting estimates and conclude that failure of this assumption to hold can result in large biases in the estimates of the error probabilities.

In this application to self-reported drug use, the estimates using the Hui-Walter independence model as well as a dependent model are compared and evaluated. The latter model is similar to the one proposed by Vacek (1985); however, it uses fewer parameters and therefore requires fewer degrees of freedom to estimate. For the dependent model, the following is assumed:

Dependent model assumptions:

(i) Homogeneous false negative probabilities

(ii) Independent and homogeneous false positive probabilities

Thus, it is assumed that a single false positive rate applies to both trials and both domains and, further, that the false positive errors are independent between both trials. Finally, it is assumed that the false negative errors are correlated between trials and that these correlations are equal for the two domains. As with the independent model, the dependent model provides for six parameters, viz all of which are estimable.

The rather restrictive assumptions regarding the false positive errors are justified because, for most of the drugs in this study, the false positive rates are expected to be quite small. In this situation, it may be reasonable to assume that to be estimated, it is hoped that the likelihood function is increased and, thus, the estimates for the more important false negative probabilities are improved.

APPLICATION OF THE HUI-WALTER METHOD TO THE NATIONAL HOUSEHOLD SURVEY ON DRUG ABUSE

In this section, the Hui-Walter method is implemented to estimate the false negative and false positive probabilities associated with the so-called recency question in the NHSDA. The recency question asks respondents about the most recent time they used a particular drug. For this study, the measurement bias for this question was evaluated for alcohol, marijuana, and cocaine. By design, the NHSDA contains many redundant questions regarding drug use recency, particularly lifetime use. Because of this redundancy, the application of the Hui-Walter method to estimate NHSDA misclassification error is possible. In this section, the use of this methodology for assessing the accuracy of self-reports is demonstrated and the characteristics exhibited by the Hui-Walter estimates are critically examined.

Description of the NHSDA

The NHSDA is a multistage, household survey designed to measure the population's current and previous drug use activities. The 1993 survey was the 13th study conducted in a series initiated in 1971. Since 1990, the survey has been conducted annually, with distinct samples of households and persons selected each year. In October 1992, sponsorship of the survey was transferred from the National Institute on Drug Abuse (NIDA) to the Substance Abuse and Mental Health Services Administration, Office of Applied Studies (SAMHSA/OAS), where it currently resides.

For this research project, data from the 1991, 1992, and 1993 surveys were used in the analysis, a total of 88,000 interviews. Subsequent discussions of the NHSDA will be restricted to design and implementation issues related to these surveys.

Survey Design and Data Collection. The NHSDA is based on a national probability sample of dwelling units in the United States. For the 1991, 1992, and 1993 studies, approximately 118 primary sampling units (PSUs) were selected at the first stage of sampling. These PSUs represent geographic areas in the United States; generally defined as counties, groups of counties, or metropolitan statistical areas (MSAs). At the second stage of selection, smaller geographic areas—segments— within each PSU were selected. The NHSDA segments were defined by joining adjacent census blocks within each PSU. At the third stage of selection, a sample of dwelling units was selected within each segment and a resident of each occupied, sampled

dwelling unit was asked to participate in a screening interview for this survey. Results from this personal visit, screening interview are used to randomly select up to two members of each household. Each selected person was then asked to participate in the personal visit, interview phase of the survey. Data on a person's current and previous drug use activities were collected during this interview phase of the survey.

The target population includes persons 12 years old or older who live in households, certain group quarters (e.g., college dormitories, homeless shelters), and civilians living on military installations. Active military personnel and most transient populations, such as homeless people not residing in shelters, were not included. The sample for the 1991, 1992, and 1993 surveys was approximately 30,000 persons each year. Hispanics, blacks, younger persons, and the residents of six the MSAs were oversampled to ensure that the sample sizes were adequate to produce the subpopulation estimates of interest.

Drug and demographic data were collected from each respondent during the interview phase using a combination of interviewer-administered and self-administered instruments. On average, the interview took about an hour to complete. It began with a set of interviewer-administered questions designed to collect data on the respondent's current and previous use of cigarettes and other forms of tobacco. These initial questions allowed the respondent to become familiar with the format of the NHSDA questions.

The remainder of the questionnaire was divided into sections corresponding to each drug of interest: alcohol; the nonmedical use of sedatives, tran-quilizers, stimulants, and analgesics; marijuana; inhalants; cocaine; crack; hallucinogens; and heroin. For each section, the interviewer gave the respondent an answer sheet and asked that responses be recorded on it. Depending on the complexity of an answer sheet, the interviewer either read the questions to the respondent or, if preferred, the respondent read the questions. Upon the completion of an answer sheet, the respondent was requested to place it in an envelope without allowing the interviewer to see the responses. The motivation for conducting the interview in this manner was to ensure that the respondent understood the questions, did not erroneously skip over major parts of the questionnaire and, more important, to guarantee response privacy.

Most of the answer sheets were designed so that even respondents who have never used a particular drug still needed to answer each question about the drug. Since both users and nonusers of a drug were asked to respond to essentially the same number of questions, the interviewer was less likely to guess that the respondent was a user or nonuser based on the time the respondent took to complete an answer sheet. This was another feature of the survey that was designed to protect the privacy of the respondent. In addition, some respondents who indicated that they never used the drug under direct questioning would later answer an indirect question about it in a way that implied use. This redundancy in the questionnaire, therefore, provided additional information regarding drug use that could be used to compensate for underreporting for the direct question.

Data Editing and Estimation. The raw NHSDA data are extensively edited to ensure the internal consistency of drug use responses. For the 1991, 1992, and 1993 surveys, this editing was based on a "most-recent- indication-of-use" rule. As described in the previous section, all respondents were required to respond to essentially the same questions regardless of their drug use. Consequently, use of a particular drug during a particular reference period could be logically established from responses to various questions. These questions included items presented on the specific drug answer sheet, as well as several items on the other answer sheets asking about general drug use activities.

For any particular drug, the logical editing begins with the drug recency question, a question at the beginning of each drug answer sheet that asks respondents about the most recent time they used a particular drug. As an example, on the alcohol answer sheet the recency question is:

> *When was the most recent time that you had an alcohol drink, that is, of beer, wine, or liquor or a mixed alcoholic drink?*
>
> Within the past month (30 days)
> More than 1 month ago but less than 6 months ago
> 6 or more months ago but less than 1 year ago
> 1 or more years ago but less than 3 years ago
> 3 or more years ago
> Never had a drink of beer, wine, or liquor in your life

Thus, the recency question was used to establish the most recent time a drug was used. At this first stage of editing, the recency response

categories are collapsed; for each drug, the respondents are classified into one of the following mutually exclusive categories: a past-month user, past-year user, lifetime user (i.e., any indication of use), or not a lifetime user of the drug under question. Under these editing rules, past-year users do not include past-month users and lifetime users do not include past-year nor past-month users.

After this recoding is completed, it is checked against the responses to all other questions from which drug recency can be implied. These questions include questions related to drug use that are asked on the specific drug answer sheet, as well as questions asked on the drug use activities answer sheets. For example, alcohol use can be implied from other questions on the alcohol answer sheet such as:

- *About how old were you when you first began to drink beer, wine or liquor once a month or more often?* [This question can be used to establish lifetime use of alcohol.]

- *On the average, how often in the past 12 months have you had any alcoholic beverage, that is, beer, wine or liquor?* [This question can be used to establish past year use of alcohol.]

- *What is the most you had to drink on any one day you drank beer, wine or liquor during the past 30 days?* [This question can be used to establish past month use of alcohol.]

Alcohol use also can be implied from questions on the drug use activities answer sheets such as:

- *During the past 12 months, have you gotten any treatment for drinking—such as from a clinic, self-help group, counselor, doctor or other professional?* [From the treatment answer sheet.]

- *During the past 12 months, for which drugs have you consciously tried to cut down on your use?* [From the drugs answer sheet.]

- *In the past 12 months, I felt aggressive or cross while drinking? (Y/N)* [From the drinking experiences answer sheet.]

In almost all cases where there is disagreement between the recency response and the responses to the other questions, the NHSDA editing rules dictate the respondent's final status should be changed to the most recent indication of use. If a response to some other question indicates use in a later recency period, then generally the response to the other question is deleted, and a bad data indicator response is put in its place. Because of this editing phase, a person's most recent use of any drug is determined by looking at all related questions and selecting the response for the most recent use. Unless otherwise noted, drug use estimates produced from the NHSDA are created using these edited most-recent- indication-of-use responses.

By the nature of the editing process, there is the potential for over-correcting for the negative bias in recency estimates and actually over-estimating drug use prevalence for some subgroups. At this writing, work was underway on the 1994 NHSDA to reevaluate the effects of the editing procedures. In addition, comparisons of the Hui-Walter estimates of prevalence—which are adjusted for both false negative and false positive responses—with the usual NHSDA estimates will provide important information regarding the net biases in the NHSDA estimates.

Results of the Hui-Walter Estimation

This analysis of the 1991-1993 NHSDA data is confined to three drugs—alcohol, marijuana, and cocaine. For each analysis, y_1 and y_2 are defined as follows.

and

As required by the Hui-Walter procedure, two domains were defined for estimation: smokers and nonsmokers. This partitioning of the population seems to satisfy the dual criteria that the difference between the drug prevalence rates for the two domains is large—drug use among smokers tends to be considerably greater than among nonsmokers; and the assumption of equality of misclassification probabilities between the two groups is tenable.

Because y_1 and y_2 are collected in the same interview, the Hui-Walter independence model would not seem appropriate because respondents who intentionally falsify their response to the recency question would likely consistently falsify their reports throughout the questionnaire. However, because subsequent questions regarding lifetime use are less direct than the recency question, it is possible that some lifetime users who falsify on the recency question may unintentionally indicate lifetime use. Then, too, some recency question falsifiers may find the less direct questions on drug use less intimidating and may respond truthfully. There is also the potential that some lifetime users who responded "no lifetime use" in the recency question due to forgetfulness may remember later in the interview and then indicate some use.

Even accepting that some inconsistencies in the responses y_1 and y_2 are likely, the assumption that these inconsistencies satisfy the independence assumption is still questionable. Therefore, these data have been analyzed using both the Hui-Walter independence model and the dependent model assumptions; both set of results are reported.

This development of the Hui-Walter methodology for self-reported drug use is still very much in its preliminary stages. In the analyses presented here, the main objective is to investigate some capabilities and limitations of the methodology and demonstrate its use for surveys such as the NHSDA for which repeated measures are available. For this objective, the usefulness of the methodology for estimating measurement bias is critically evaluated and additional applications in the field of drug use measurement are suggested. It is possible that while the Hui-Walter false positive and negative rates are biased, their relative magnitudes still provide important insights about the causes and remedies of measurement error by identifying the socioeconomic subpopulations, data-collection procedures, and survey designs that are most prone to measurement error.

The more than 88,000 interviews collected in the 1991-93 NHSDA surveys were the object of these analyses. Table 1 gives the results of

the analysis for alcohol, marijuana, and cocaine. Note that in this table the false negative rates for the dependent model are generally larger than those for the independent model. This is expected because, as Vacek (1985) has shown, positive between-trial correlations result in a downward bias in the estimated error rates under the independence model. Recall that for the dependent model, only between-trial independence for the false positive errors was assumed. Further, the dependent model provides only one parameter, , for the false positive rate. The result is a rate that is an average of and Because is usually much smaller than in the independent model, the result is also expected that for the dependent model is usually less than for the independent model.

The pattern exhibited by the prevalence estimate it is also noteworthy, viz., in almost all cases

As anticipated, the estimate of " from the recency question appears to be biased downward, the bias being greatest when the false negative rate is largest. Since estimates of for the dependent model are usually larger than for the independent model, it is also anticipated that is usually less than . Note also that since the NHSDA estimator does not take into account the possibility of false positive errors, it is not surprising that . Finally, it is possible that .

Let y_i denote the final edited classification for respondent *i*. Recall that the NHSDA estimator assigns $y_i = 1$ to any individual *i* for whom either y_1 or y_2 is 1. Further, if both y_1 and y_2 are 0, the NHSDA estimator assigns $y_i = 0$ to the respondent. However, the Hui-Walter estimator estimates the proportion of respondents in the population who are truly 1s though both y_1 and y_2 are 0. Thus, when these respondents are added to the number of 1 responses, it is possible for the Hui-Walter estimator to produce estimates that are larger than the NHSDA estimates, as can be observed from table 1.

Finally, the validity of the Hui-Walter estimates is considered; attention is given to degree to which the Hui-Walter estimates of measurement bias are themselves biased. Unfortunately, the evaluation of the bias in

TABLE 1. *Comparison of independent and dependent Hui-Walter estimates for the 1991-1993 NHSDA.*

Characteristic	False negative rate				False positive rate				Estimate prevalence rate (as a percent)			
	Independent		Dependent		Independent		Dependent					
	%	S.E.	%	S.E.	%	S.E.	%	S.E.	$\hat{\pi}_{INDE}$	$\hat{\pi}_{DEP}$	$\hat{\pi}_{RECENCY}$	$\hat{\pi}_{NHSDA}$
Lifetime alcohol use												
Total	1.343	(0.106)	1.780	(0.053)	0.002	(0.001)	0.083	(0.279)	83.94	84.31	82.82	84.33
Race/ethnicity												
Hispanic	1.941	(0.294)	3.149	(0.142)	0.193	(0.082)	0.212	(0.089)	76.28	77.23	74.85	77.33
Black	1.971	(0.303)	3.228	(0.157)	0.000	(0.000)	0.764	(0.151)	75.74	76.56	74.25	76.91
White/other	1.207	(0.134)	1.450	(0.063)	0.000	(0.000)	0.000	(0.000)	86.12	86.33	85.08	86.33
Age group												
12-17	0.881	(0.427)	5.671	(0.278)	0.328	(0.085)	0.413	(0.069)	39.97	41.99	39.82	42.47
18-25	0.703	(0.164)	1.482	(0.092)	0.000	(0.000)	0.000	(0.000)	87.50	88.19	86.88	88.19
26-34	1.131	(0.173)	1.114	(0.077)	0.000	(0.000)	0.606	(0.238)	92.72	92.66	91.67	92.75
35+	1.725	(0.101)	1.725	(0.102)	0.000	(0.000)	0.000	(0.000)	88.09	88.09	86.57	88.09
Gender												
Male	1.390	(0.146)	1.620	(0.072)	0.353	(0.109)	0.368	(0.112)	88.26	88.46	87.07	88.55
Female	1.288	(0.159)	1.924	(0.072)	0.000	(0.000)	0.000	(0.000)	79.95	80.46	78.92	80.46

KEY: * = Indicates estimate not available.

TABLE 1. *Comparison of independent and dependent Hui-Walter estimates for the 1991-1993 NHSDA (continued).*

Characteristic	False negative rate				False positive rate				Estimate prevalence rate (as a percent)			
	Independent		Dependent		Independent		Dependent					
	%	S.E.	%	S.E.	%	S.E.	%	S.E.	$\hat{\pi}_{INDE}$	$\hat{\pi}_{DEP}$	$\hat{\pi}_{RECENCY}$	$\hat{\pi}_{NHSDA}$
Lifetime marjuana use												
Total	0.594	(0.229)	3.384	(0.108)	0.011	(0.006)	0.014	(0.008)	33.21	34.17	33.02	34.18
Race/ethnicity												
Hispanic	1.538	(0.841)	5.439	(0.000)	0.003	(0.018)	0.003	(0.021)	27.11	28.23	26.70	28.23
Black	0.997	(0.638)	3.769	(0.261)	0.082	(0.032)	0.099	(0.037)	31.68	32.60	31.42	32.73
White/other	0.480	(0.334)	3.101	(0.142)	0.001	(0.312)	0.003	(0.012)	34.60	35.53	34.43	35.54
Age group												
12-17	0.523	(0.912)	4.711	(0.468)	0.003	(0.013)	0.006	(0.024)	10.68	11.15	10.62	11.16
18-25	0.940	(0.235)	•	•	0.016	(0.024)	0.023	(0.036)	48.72	55.41	48.27	49.10
26-34	0.355	(0.293)	1.175	(0.098)	0.037	(0.032)	0.043	(0.036)	60.23	60.73	60.03	60.76
35+	•	•	0.000	(0.000)	0.007	(0.017)	1.007	(0.060)	25.19	25.16	25.17	26.66
Gender												
Male	1.208	(0.320)	3.338	(0.151)	0.016	(0.013)	0.019	(0.015)	38.59	39.44	38.13	39.46
Female	0.000	(0.000)	0.000	(0.000)	0.007	(0.027)	0.720	(0.033)	28.36	28.36	28.37	29.39

TABLE 1. *Comparison of independent and dependent Hui-Walter estimates for the 1991-1993 NHSDA (continued).*

Characteristic	False negative rate				False positive rate				Estimate prevalence rate (as a percent)			
	Independent		Dependent		Independent		Dependent					
	%	S.E.	%	S.E.	%	S.E.	%	S.E.	θ_{INDE}	θ_{DEP}	$\theta_{RECENCY}$	θ_{NHSDA}
Lifetime cocaine use												
Total	3.652	(0.471)	5.314	(0.230)	0.005	(0.004)	0.006	(0.004)	11.62	11.83	11.20	11.84
Race/ethnicity												
Hispanic	1.631	(1.699)	6.915	(0.553)	0.000	(0.000)	0.000	(0.000)	10.17	10.75	10.01	10.75
Black	6.027	(1.177)	8.983	(0.672)	0.003	(0.201)	0.005	(0.076)	9.67	9.98	9.09	9.99
White/other	3.471	(0.634)	4.717	(0.000)	0.005	(0.007)	0.005	(0.007)	12.29	12.45	11.87	12.46
Age group												
12-17	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.190	(0.023)	1.36	1.36	1.36	1.74
18-25	3.763	(0.671)	4.906	(0.000)	0.003	(0.015)	0.004	(0.017)	15.64	15.83	15.05	15.83
26-34	0.713	(0.723)	1.935	(0.196)	0.032	(0.019)	0.036	(0.021)	26.43	26.76	26.27	26.81
35+	6.182	(1.766)	8.299	(0.000)	0.000	(0.000)	0.000	(0.000)	8.03	8.21	7.53	8.21
Gender												
Male	4.904	(0.672)	5.271	(0.000)	0.011	(0.009)	0.011	(0.010)	14.75	14.81	14.04	14.83
Female	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.271	(0.018)	8.63	8.63	8.63	9.12

KEY: * = Indicates estimate not available.

the estimators of the error probabilities and " requires knowledge of the true error probabilities, which is not available. Sinclair (1994) and Sinclair and Gastwirth (1993) examine the sensitivity of the estimates to violations in the model assumptions. For the independent model, they found that the estimates are highly sensitive to violations of the independence assumptions. Moderately large positive correlations between errors in the two measurements can lead to substantial negative biases in the estimates of the error probabilities. Similarly, violations of the between-domain homogeneity assumption can also bias the Hui-Walter estimates; however, differences in the error rates as high as 20 percent between the two domains did not appear to bias the estimates of " appreciably. Since the dependent error model assumes homogeneity between domains but does not assume independence for the false negative errors, the results of Sinclair and Gastwirth (1993) support the claim that the dependent model estimates have greater validity than the independent model estimates.

Another indicator of the validity of the estimates is the degree to which the patterns of errors across demographic variables and the magnitudes of the estimated error rates agree with those in the published literature. Many articles attest to the high potential of underreporting for drug use self-reports, particularly among arrestee reports (see, for example, Mieczkowski 1991; General Accounting Office 1993). These researchers would tend to support the higher estimates of false negative error observed for the dependent error model rather than the smaller estimates produced by the independent model. However, since the true false negative and false positive error probabilities for the NHSDA are unknown, the existing literature is insufficient for assessing the magnitudes of the biases in the error rates obtained from either the dependent or the independent model.

Besides the question of the bias in the estimates, one can, to some extent, investigate the question of the relative validity of the Hui-Walter estimates; that is, the extent to which the estimates of misclassification error provide information regarding the relative bias in self-reports across socioeconomic classes and geographic regions, and for alternate drugs of abuse. For this analysis, the results from Fendrich and Vaughn (1994), who estimated the denial rates for the National Longitudinal Survey of Youth (NLSY) cohort, were used. For nine socioeconomic variables, they computed the proportion of respondents who admitted to using a drug (marijuana or cocaine) in the 1984 survey and then denied ever using the drug in the 1988 survey.

The NLSY is a nationally representative longitudinal sample of 12,686 individuals who were ages 14 to 21 when they were first interviewed in 1979. Twelve waves of interviews were conducted between 1979 and 1990 for the sample analyzed by Fendrich and Vaughn. Retention rates averaged about 90 percent in each of the survey years. Questions about illicit substance use were asked in 1980, 1984, and 1988. In 1988, an experiment was conducted in which half the subjects (in a selected sample) were randomly assigned to an interviewer-assisted mode and the other half to the self-administered mode.

The focus of Fendrich and Vaughn's study is on responses to the surveys administered in 1984 and 1988, since these two surveys included nearly identical questions about lifetime use for two illicit drugs—cocaine and marijuana. Their study considers two subsamples as follows: all respondents who completed the questions about marijuana use in 1984 and 1988 and also reported lifetime use of marijuana in 1984 (N = 6,204); and all respondents who completed the questions about cocaine use in 1984 and 1988 and also reported lifetime use of cocaine in 1984 (N = 1,589).

Although denial rates estimated by Fendrich and Vaughn provide direct evidence of false negative error in the NLSY, they should not be taken as estimates of the false negative probabilities because they refer only to respondents who reported any use of a drug in the first interview. Thus, the rates exclude persons who used the drug but did not report their use and respondents who never used the drug but reported that they did in the first interview.

Further, the magnitudes of the Fendrich and Vaughn denial rates are not useful for predicting the magnitudes of the NHSDA false negative error rates for a number of reasons. First, they are denial rates, not false negative rates. Second, the interview setting and mode in the NLSY are quite different from the NHSDA. While the NLSY is a panel study in which the interviewer returns annually to reinterview the respondents and may become quite familiar with them, the NHSDA is a one-time cross-sectional survey in which the interviewer and respondent have never met before. In the NHSDA, great care is taken to preserve the anonymity of the respondents and to protect their responses from discovery by the interviewer. In the NLSY, this type of confidentiality is not possible because of the nature of the survey. Finally, in the NLSY, the two measurements were separated by a period of 4 years, while in the NHSDA, the two measurements were separated by only a few minutes. Thus, in the NLSY, there is a

greater chance that the respondent's response on measurement 1 will change by the time measurement 2 is taken.

Despite these limitations of comparisons between the NHSDA and the NLSY estimates, such comparisons may still be quite fruitful. To the extent that the denial rates estimated in Fendrich and Vaughn reflect general tendencies of various socioeconomic domains to underreport their drug use, and to the extent that these tendencies and patterns for underreporting are stable over time, the estimates of false negative rates from NHSDA should be correlated, to some extent, with the denial rates from the NLSY for the same subpopulations. Lack of concordance between the two sets of estimates may not be evidence of the invalidity of either set of estimates for the reasons cited above. However, significant correlations between the two estimates are evidence of the validity of both sets of estimates as measures of the relative true-false negative error in self-reported drug use in surveys.

Table 2 shows Fendrich and Vaughn's NLSY denial rates, the NHSDA independent model false negative error estimates (NHSDA-IND), and the NHSDA dependent model false negative error estimates (NHSDA-DEP). Note first that the NLSY denial rates are considerably larger than both sets of NHSDA estimates. However, what is important here is the correlation between the NLSY and the NHSDA estimates. Table 3 displays the correlations for all pairs of the three sets of estimates for marijuana and cocaine. The "across variables" correlation is Corr (NLSY, NHSDA) across all 29 variable categories shown in table 2. The NHSDA-INDEP estimates exhibited highly significant correlation with NLSY denial rates for both marijuana (0.76) and cocaine (0.58). Surprisingly, the across variables correlations for the NHSDA-DEP estimates are not significant. The "within variables" correlation is the average correlation between categories within each of the nine variables in table 2. Here, both the NHSDA-INDEP and the NHSDA-DEP estimates exhibit highly significant correlations with the NLSY estimates for cocaine, while for marijuana the correlations are not distinguishable from 0. These results support the validity of the Hui-Walter estimates when viewed as measures of relative bias (between socioeconomic domains).

Characteristic	Marijuana (percent)			Cocaine (percent)		
	NLSY	NHSDA-IND	NHSDA-DEP	NLSY	NHSDA-IND	NHSDA-DEP
Total 23-32 year olds	11.7	0.77	1.38	18.9	1.72	48.07
Privacy						
Private interview	12.5	0.93	0.38	18.6	1.50	2.17
Others present	10.3	0.55	0.39	22.1	1.93	2.36
Race/ethnicity						
Hispanic	14.9	2.58	3.40	20.8	0.85	3.21
Black	19.3	2.66	2.87	33.2	3.99	6.79
White/other	8.0	0.38	0.99	15.0	1.55	1.66
Gender						
Male	11.3	0.90	*	19.4	1.79	*
Female	12.2	0.62	1.40	18.3	0.00	0.00
Income						
0-$11,999	15.0	0.65	2.57	19.7	0.35	2.85
$12,000 - $19,999	11.1	0.57	0.92	20.3	2.46	3.10
$20,000 - $29,999	10.6	1.38	1.49	16.5	0.55	2.45
$30,000 - $42,999	10.2	0.49	1.53	22.4	0.74	1.48
$43,000+	9.0	0.16	0.61	22.6	0.11	2.00

KEY: * = Indicates estimate not available.

Characteristic	Marijuana (Percent)			Cocaine (Percent)		
	NLSY	NHSDA-IND	NHSDA-DEP	NLSY	NHSDA-IND	NHSDA-DEP
Education						
< High school	15.4	1.56	2.09	26.6	1.99	3.18
High school	11.6	0.29	1.69	18.9	0.56	2.92
Some college	11.3	0.56	0.88	18.7	0.16	1.14
College graduate	8.3	0.00	0.00	12.8	0.19	0.00
Labor force						
Employed	11.2	0.68	1.40	18.3	0.22	1.86
Unemployed	12.3	1.26	1.26	22.8	3.74	3.74
Not in labor force	14.6	0.77	1.35	19.7	1.44	3.39
Marital status						
Single	11.7	0.89	1.66	17.5	2.21	2.39
Married	11.8	0.78	1.28	22.1	1.58	2.45
Widowed/div/sep	11.6	0.46	1.06	14.3	0.22	1.22
Residency						
Urban	11.7	0.86	10.56	17.9	1.78	2.46
Rural	11.7	0.57	0.90	25.0	1.27	1.27
Age						
23-25	11.7	1.22	1.81	21.4	3.09	3.09
26-27	12.4	0.49	0.63	19.7	0.92	2.36
28-29	11.4	0.72	1.16	17.6	1.40	1.94
30-32	11.3	0.52	1.62	16.6	0.00	0.00

KEY: * = Indicates estimate not available.

TABLE 3. *Correlational analysis of NHSDA false negative rates and NLSY denial rates for characteristics in Fendrich and Vaughn (1994).*

Correlation	Marijuana		Cocaine	
	Across var. (N = 29)	Within var. (N = 9)	Across var. (N = 29)	Within var. (N = 9)
NHSDA-IND with NLSY	0.76*	0.28	0.58*	0.57*
NHSDA-DEP with NLSY	0.06	0.01	0.02	0.55**
NHSDA-IND with NHSDA-DEP	0.15	0.41***	0.19	0.87***

KEY: * = Significant at = 0.05; ** = significant at = 0.01; *** = significant at = 0.001.

SUMMARY AND CONCLUSIONS

In this chapter, a general model for studying misclassification in self-reported drug use was presented and the model was then extended to the case where two measurements of the same characteristic are available for a the sample of respondents. For the two-measurements case, the general model requires seven parameters while only 3 degrees of freedom are available for estimation. Thus, some additional assumptions are required to reduce the set of unknown parameters to three or less. It was shown how the assumptions typically made for test-retest, true value, improved value, and Hui-Walter methods relate to the general model. Further, it was shown how the measures of reliability, measurement bias, estimator bias, mean squared error, false negative, and false positive probability can be defined in the context of the general model and how they may be estimated under the appropriate study designs.

Finally, the use of Hui and Walter's method for estimating misclassification error based upon two erroneous reports was demonstrated. The reports may be self-reports, biological tests, administrative record values, or any other measure. For the general case of two measurements, the Hui-Walter method used maximum likelihood estimation to obtain estimates of the false negative and

false positive probabilities associated with each measurement as well as the error adjusted estimates of prevalence based upon both measurements. The method requires that the population be divided into two domains that have markedly different prevalence rates and that satisfy the assumption of homogeneity of error probabilities.

To demonstrate the use of the Hui-Walter method for evaluating the error in self-reported drug use, the method was applied to the 1991-93 NHSDA data. Two sets of model assumptions were evaluated: the independent model and the dependent model. The dependent model yielded estimates of false negative error that were generally larger than those for the independent model. Further, the dependent model produced estimates of drug use prevalence that were very nearly the same as the NHSDA published estimates. However, an important advantage of the Hui-Walter method is that it has a probability basis for the estimation that is lacking in the NHSDA estimation procedure. In addition, the Hui-Walter estimators are adjusted for false positive errors and consistent false negative errors, while the NHSDA estimator ignores these errors.

To provide evidence of the validity of the Hui-Walter estimates, correlations between the NHSDA model-based estimates of false negative error and the NLSY denial rates were computed. The independent model exhibited highly significant average correlations across categories within the nine socioeconomic variables reported in Fendrich and Vaughn (1994). For cocaine, both models produced estimates that were significantly correlated with the NLSY within variables. This evidence suggests that the Hui-Walter method is at least useful for comparing false negative rates across socioeconomic subgroups within the same survey in order to identify which groups are most prone to false negative error. The available data were inadequate to determine whether the false positive and false negative error rates produced by the Hui-Walter method are unbiased for this application.

Future work in this area will include further study of the bias and validity of the Hui-Walter estimation method. As an example, in this application, the joint likelihood of smokers and nonsmokers was considered because this partitioning of the population seemed to fit the Hui-Walter criterion well. Other definitions for the two domains that also a priori seem to meet the Hui-Walter criteria will also be considered and the estimates produced by each definition will be compared. Finally, attempts will be made to relate the estimates as dependent variables to subpopulation characteristics using logistic

models that predict the false negative rate from variables such as age, race, sex, and income. In this way, the concurrent validity and predictive validity of the Hui-Walter estimates can be investigated.

Finally, the Hui-Walter method should be considered for studies of drug use reporting error that use a biological test (hair, urine, or nail) to evaluate the error in the self-report. As reported in the literature (e.g., Cone, this monograph), biological tests are themselves subject to considerable error, even when the period for drug use is restricted to maximize the accuracy of the test results. Self-report validity studies employing biological testing have assumed the true value or preferred value assumptions described earlier. However, the general two-measure- ment model in this discussion may be more appropriate for these studies. As mentioned, when the second measurement is a biological test, the assumption of between-measurement independence is likely satisfied and thus the Hui-Walter independence model can be used. Under this model, the procedure will provide estimates of false positive and false negative errors for both the self-report and the biological test result. In this way, the accuracies of both self-reports and biological tests for drug use measurement can be studied.

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