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SMALL BUSINESS DRUG-TESTING STRATEGY: IMPLICATIONS OF PRE-EMPLOYMENT TESTING

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ABSTRACT

This paper identifies problems in drug testing accuracy that may arise in small business environments in which job applicants are subjected to drug tests, and suggests a method for dealing with the problems. Relevant concepts of drug-test accuracy are reviewed. These concepts are incorporated in Bayesian analyses of data from specific workplace-applicant populations, and accuracy levels to be expected in testing of applicants in such workplaces are identified. The conclusion of this analysis is that seemingly accurate tests for abused drugs can be inaccurate to a disturbingly high degree, particularly under circumstances likely to be present in many small business drug-testing programs. A method by which these inaccuracies can be avoided is suggested.

INTRODUCTION

In 1997, approximately 8.3 million adult drug users were employed in the United States (U.S Department of Health and Human Services [DHHS], 1998). These substance-abusing workers cost their employers an additional $100 billion annually due to their lower productivity, their higher health care demands, and their higher rates of absenteeism, accidents and turnover, (Bahls, 1998; Bates, 1998b; Warner, 1996; "Workplace Substance Abuse," 1997). Small firms, in particular, suffer from the problems caused by drug-abusing workers because nearly 60 percent of employees who abuse drugs work for small businesses (Bahls, 1998; U.S. Small Business Administration, 1994; Warner, 1996; Workplace Substance Abuse, 1997).

In attempting to avoid problems associated with drug-abusing employees, the nation's large employers almost universally test job candidates for the presence of banned substances. For example, pre-employment drug screening is conducted by 95 percent of Fortune 500 companies (Bahls, 1998).

Unfortunately, smaller businesses have been less aggressive in efforts to avoid drug abusers (Aalberts, 1991; Aalberts and Walker, 1988; DHHS, 1996; Hartwell, Steele, French, and Rodman, 1996; Huneycutt and Wibker, 1989; Martinez, 1992; National Institute on Drug Abuse, 1989, 1991; Rich, 1992; Ward, 1991; Warner, 1996). Only three percent of small businesses have drug-testing programs, and virtually all testing is done during pre-employment evaluation (Bahls 1998; Godefroi and McCunney, 1988; SBA, 1994; Warner, 1996; "Workplace Substance Abuse," 1997).

Accordingly, drug abuse has become a particular problem for small businesses because drug abusers (often chronic abusers) are now gravitating to smaller businesses to avoid the testing programs at larger corporations (Bahls, 1998; Bates, 1998a; Mangan, 1992; "Workplace Substance Abuse," 1997). That is, since larger firms are more likely to have drug-testing programs, drug-abusing employees "flee to the small business side of the economy" ("Workplace Substance Abuse," 1997). "Word circulates about which employers test for drugs, and which ones don't. Those that don't 'become the employer of choice for substance abusers' " (Bahls, 1998).

Without doubt, most small-business owners and managers recognize and wish to avoid the negative consequences of hiring drug-users. For example, in a 1998 American Management Association survey in which employers were questioned about actions they would take if a job applicant were to test positive, less than one percent of the small business employers (that is, those with fewer than 500 employees) indicated that they would hire such an applicant (American Management Association, 1998).

It would seem, therefore, that in order to protect themselves against drug abusers, small businesses will soon follow their larger counterparts and increasingly conduct pre-employment drug tests of all potential employees. The benefits from drug testing are obvious, but there are also less-obvious but very real costs, both to the small businesses and to potential employees who unjustly might be identified as drug users.

That is, if the drug tests are not highly accurate, qualified job applicants may be unjustly denied employment. In such cases, the potential employee is not the only loser; the business that denied employment also loses a potentially well-qualified employee. In the current economic climate, where small businesses are competing more-and-more with major corporations for qualified employees, and where labor shortages have driven up wage costs for even marginal employees, it is extremely important to avoid the mistake of denying employment to a qualified applicant because of an erroneous result of a drug test.

In fact, small-business owners and managers have identified "finding good workers" as their most difficult problem (Hall and Tian, 1998). Because the successful implementation of strategies of small businesses are often dependent on the presence of good employees, any procedure that inadvertently weeds out such good employees is a cause for great concern. Therefore, if small businesses are to implement drug-testing programs, they must take steps to avoid false positive results that lead to rejection of truly drug-free applicants. Indeed, employers who take greater care in applicant drug testing will have an edge on their competition in attracting good workers.

The accuracy of routine drug tests during pre-employment screening is the subject of this paper. The focus is on the proportion of positive drug tests that are false and how this proportion can be reduced. We review the concepts of accuracy that are most relevant, and apply these concepts to data on drug usage by applicants in different types of workplaces, thereby identifying the potential magnitude of erroneous positive test results (which we refer to as the false accusation rate) that could occur in routine pre-employment drug-testing programs. The clearest conclusion of this analysis is that seemingly accurate tests for abused drugs can be inaccurate to a disturbingly high degree, under circumstances likely to be present in many small business testing programs. The remainder of this paper is divided into sections that discuss terminology, drug usage rates for applicants in certain workplaces, laboratory proficiency studies, Bayesian analyses that incorporate proficiency-study data and drug-usage data, and a suggested method for avoiding unacceptable levels of inaccuracy.

TERMINOLOGY

When a specimen is tested for drugs, one of four outcomes must occur:

- a specimen with drugs tests positive for drugs (true positive)
- a specimen with drugs tests negative for drugs (false negative)
- a specimen with no drugs tests positive for drugs (false positive)
- a specimen with no drugs tests negative for drugs (true negative)

A specimen that contains drugs must test either positive or negative. That is, the probability of a positive test result (given that drugs are present) plus the probability of a negative test result (given that drugs are present) must equal 1.0. This may be written:

$$P(+|\text{Drugs}) + P(-|\text{Drugs}) = 1.0$$

In other words, when drugs are present in a specimen, a drug test will yield either a true positive or a false negative result, and the probabilities of a true positive and a false negative must total one.

Similarly, a specimen which does not contain drugs must test either positive or negative. That is, when no drugs are present, the test must yield either a false positive or a true negative. This may be written:

$$P(+|\text{No Drugs}) + P(-|\text{No Drugs}) = 1.0$$

We are most concerned with incorrect results, that is, with false positives and false negatives. The probability of obtaining a false positive, $P(+|\text{NoDrugs})$, is called the *false positive rate*, and the probability of obtaining a false negative, $P(-|\text{Drugs})$, is called the *false negative rate*. Drug testing procedures, therefore, should attempt to minimize false positive and false negative rates.

Another important concept is the *false accusation rate*. The false accusation rate is the probability that *no* drug is present in a specimen, given that the test yielded a positive result:

$$\text{False Accusation Rate} = P(\text{No Drugs}|+)$$

For example, if 90 out of every 100 people who test positive truly have drugs in their systems, and 10 do not, then the probability that persons with positive test results truly do not have drugs in their systems would be 0.10. That is, such a drug test would have a false accusation rate of 10 percent.

The importance of this concept is readily apparent, because it is the key to determining whether a positive result on a drug test provides sufficient evidence of drug usage. If, for example, positive results on a test are expected to be untrue in one out of every four cases, then a positive test usually would not be considered reliable evidence of drug use. More importantly, if one wishes to protect the innocent from false accusation (and, thereby, avoid improperly rejecting a potentially good employee), then it is the false accusation rate of the test that is of prime concern.

DRUG USAGE RATES

Not surprisingly, estimates of drug usage vary widely. Many of those making pronouncements about the extent of drug abuse have strong incentives to show that drug usage is at one extreme or the other. Moreover, the characteristics of the group about which the estimates are made can cause wide variations, because drug usage varies significantly based on age, geographic location, and other variables. Considering these caveats, we provide several estimates of the extent of drug use in the population and in various workplaces typical of small businesses.

The National Household Survey on Drug Abuse estimates that 6.1 percent of the U.S. population 12 years old and older used some illicit drug at least once during the month prior to the household survey (DHHS, 1998). Another study by DHHS provides statistics regarding drug usage rates in various industries (Hoffman, Larison, and Brittingham, 1996). In retail trade, approximately 11 percent of full-time employees admitted to having used illegal drugs within the past 30 days, and nearly 20 percent indicated that they had used illegal drugs sometime during the past year. In wholesale trade, eight percent of full-time employees admitted to having used illegal drugs in the past 30 days, and more than 15 percent indicated that they had used illegal drugs sometime during the past year.

The Hoffman et al. (1996) study indicates that nearly 12 percent of full-time construction workers reported illicit drug use in the past 30 days, and approximately 22 percent indicated they had used illegal drugs sometime during the past year. In the hotel/motel industry, more than nine percent of employees admitted to using illegal drugs within the past 30 days, and 17 percent indicated they had used illegal drugs sometime during the past year. Approximately 15 percent of workers in the manufacturing industry admitted to illegal drug use sometime during the past 12 months. On the other hand, police and detectives had the lowest reported level of illicit drug use (one percent), while administrative support staff, teachers, child care workers, computer programmers, and engineers also reported low drug usage rates.

ACCURACY OF DRUG TESTING

Because of the need for accurate tests, numerous studies of drug testing laboratory proficiency have been conducted in the United States and other countries. In such proficiency tests, prepared samples are sent to laboratories to determine the accuracy of the laboratory testing procedures (Barnum and Gleason, 1999). In this article, we use data from the most recent (published) proficiency study conducted in the United States (Knight et al., 1990). In their study, proficiency tests of laboratories used by Rockwell International were conducted. Commercially prepared samples containing drugs of abuse were disguised as routine submissions to testing laboratories used by nine Rockwell facilities. Because the samples were disguised as routine submissions, these were blind tests; that is, the laboratories were not aware that they were being tested.

The Knight et al. (1990) study yielded a two percent false positive rate and a 20 percent false negative rate—rates which the authors indicate are similar to those found in other blind studies. The errors were not limited to a particular testing technique, to a particular drug, or to a particular laboratory. Among the conclusions of the study was that there is a need for routine blind testing programs to ensure that employers can rely on the results of drug tests when making decisions about hiring and disciplinary actions.

The false positive rate of two percent indicates a 0.02 probability of a false positive result, which is an estimate of P(+|NoDrugs). Similarly, the false negative rate of 20 percent indicates a 0.20 probability of a false negative result, which is an estimate of P(-|Drugs). *It* *should be emphasized that the error rates in the Knight et al. (1990) study resulted from a test protocol which included confirmation tests as follow-ups to initial screening tests that yielded positive results.* That is, a determination of a positive test result required both a positive result on a screening test, followed by a positive result on a confirmation test. The importance of confirmation tests, which most often are *not* used by small businesses, is discussed later.

BAYESIAN ANALYSIS

Employers should take reasonable care to ensure that qualified applicants are not eliminated from consideration for a position as a result of questionable drug-test results. As noted above, the most recently-reported laboratory proficiency study conducted in the United States (Knight, et al., 1990) yielded a false positive rate of two percent, which suggests that 98 percent of drug-free applicants test negative. Accordingly, many employers would conclude that there is clear and convincing evidence that an applicant who tests positive has used illegal drugs.

However, these results are not what they seem. For example, consider a group of 10,000 applicants who are tested for drug usage. If 11 percent of the group are truly taking drugs, then 10,000 * 0.11 = 1,100 will provide urine specimens that contain drugs, and the remaining 8,900 will provide specimens that are drug-free. Of the specimens containing drugs, 1,100 * 0.20 = 220 will test negative for drugs (based on the 20 percent false negative rate reported by Knight et al. (1990)), and the remaining 880 will test positive. Likewise, of the specimens not containing drugs, 8,900 * 0.02 = 178 will test positive for drugs (based on the two percent false positive rate reported by Knight et al.), and the remaining 8,722 will test negative. Thus, a total of 880 + 178 = 1,058 specimens will test positive for drugs, although 178 of these 1,058 do not actually contain drugs. Therefore, 178/1,058 = 0.168 (or 16.8 percent) of those testing positive for drug usage truly will be drug free.

Thus, despite the low (two percent) false positive rate, one out of every six applicants who test positive will truly be drug free! It would seem illogical, from the standpoint of good personnel practice, to eliminate an applicant on the basis of such unreliable evidence.

These results, and other examples based on differing rates of drug use and of drug-test accuracy, can be developed more formally by Bayesian analysis. Bayesian analysis deals with problems of decision making under uncertainty by combining new information with existing information in an attempt to reduce the uncertainty (Raiffa and Schlaifer, 1961; Winkler, 1972). Bayes' Theorem is used to revise initial probabilities on the basis of new information (Bayes, 1763). Although Bayes' Theorem was developed more than two centuries ago, the primary advances in the field of Bayesian analysis have occurred in the last 40 years, during which Bayes' Theorem has been used extensively in support of decision-making processes in business, government, and the service sector.

Consider the first case in Table 1, which exhibits the application of Bayes' Theorem. As shown for Case 1 in columns 2 and 3 of the table, a urine specimen must either contain drugs (S_1) or contain no drugs (S_2). For this case, it is assumed that the probability is 0.11 that a urine specimen truly contains drugs; therefore, the probability is 0.89 (1 - 0.11) that it does not contain drugs, as shown in column 4. These probabilities indicate that 11 percent of the target population uses drugs; recall that this is the estimated usage rate for retail workers in the Hoffman et al. (1996) study of drug use in the workplace.

The next column, column 5, indicates the probability of the urine specimen testing positive for drugs when there truly are drugs present (0.80), and when there truly are no drugs in the specimen (0.02). That is, $P(+|Drugs) = 0.80$, and $P(+|NoDrugs) = 0.02$. These probabilities are taken from the Knight et al. (1990) study regarding laboratory proficiency, which reported a 20 percent false negative rate (therefore, an 80 percent true positive rate) and a two percent false positive rate.

Table 1
Application of Bayesian Analysis to Drug Test Data

Case	State of Nature	State of Nature Notation S_j	Initial Probability $P(S_j)$	Conditional Probability Given S_j $P(+\|S_j)$	Probability of Positive Result Given S_j $P(+\|S_j)^* P(S_j)$	Revised Probability for the State of Nature $P(S_j\|+)$
1	Drugs	S_1	0.11	0.80	0.0880	0.832
	No Drugs	S_2	0.89	0.02	0.0178	0.168
			1.00		P(+) = 0.1058	1.000
2	Drugs	S_1	0.22	0.80	0.1760	0.919
	No Drugs	S_2	0.78	0.02	0.0156	0.081
			1.00		P(+) =0.1916	1.000
3	Drugs	S_1	0.01	0.80	0.0080	0.288
	No Drugs	S_2	0.99	0.02	0.0198	0.712
			1.00		P(+) =0.0278	1.000

The numbers in the sixth column are the products of the numbers in the two previous columns. That is, for the population being tested, the joint probability that a person truly is on drugs and tests positive for drugs is 0.0880, while the probability that a person truly is not on drugs but tests positive for drugs is 0.0178. Note that the sum of these two probabilities, denoted by P(+) and equal to 0.1058, is the probability of a positive test result.

Dividing each of the numbers in the sixth column by P(+) yields the numbers in the seventh column, which are the probabilities of the particular states (that is, Drugs and No Drugs), given a positive test result. Thus, the probability that specimens that test positive will truly contain drugs is 0.832. And, the probability that specimens that test positive will contain no drugs is 0.168. That is, P(Drugs|+) = 0.832, and P(No Drugs|+) = 0.168. Accordingly, we may consider the testing process to yield a *false accusation rate* of 0.168; that is, approximately 17 out of 100 people who test positive will be falsely identified as drug users.

The actual probability that an applicant is not on drugs, even though he/she tested positive, will vary depending on: (a) the percentage of the applicants that truly are taking drugs, (b) the test false positive rate, and (c) the test false negative rate. Two additional situations are presented in Cases 2 and 3 in Table 1.

Recall that in Case 1 we assumed that 11 percent of the population being tested actually had drugs in their systems. In Case 2 and Case 3, we use different estimates of the proportion of the target population on drugs. While Case 1 used a drug usage rate (11 percent) equal to that for retail workers estimated by Hoffman et al. (1996), Case 2 uses the higher 22 percent rate Hoffman et al. estimated for construction workers, and Case 3 uses a lower rate (approximately 1 percent) similar to the Hoffman et al. estimate for populations such as police, child care workers, engineers, and computer programmers.

As seen in column 7 of Table 1, the false accusation rates are 16.8 percent in Case 1, 8.1 percent in Case 2, and 71.2 percent in Case 3. Thus, for Case 1, approximately one out of every six positives represents a job applicant who has not taken drugs but yields a positive test result. For Case 2, one out of every twelve positives represents a drug-free applicant who yields a positive test result; and, for Case 3, more than 7 out of 10 positives represent drug-free applicants who yield positive test results. Under any of these circumstances, if these results lead to the denial of employment, many drug-free applicants will experience injustices, and employers will needlessly lose the opportunity to hire valuable employees.

Moreover, for illustrative purposes in our Bayesian analysis, we used false positive and false negative rates from the Knight et al. (1990) study, and those rates were based on drug testing processes that included confirmation testing. That is, all initial positive results were confirmed by using a more accurate confirmation test. However, as noted previously, most small business drug testing occurs in the pre-employment venue, and such tests are often *not confirmed.* This lack of confirmation testing can prove problematic (Zurer, 1997). *Accordingly, pre-employment screening tests can be expected to be much less accurate than confirmed tests, and the reduced level of test accuracy can be expected to yield Bayesian results which are significantly worse (in terms of false accusation rates) than those developed herein.*

For example, suppose that an unconfirmed testing process yields a false positive rate of five percent, rather than the two percent rate used in our analysis. Then the false accusation rate for Cases 1, 2, and 3 will be 33.6 percent, 18.1 percent, and 86.1 percent, respectively. That is, for Case 1, approximately 1 out of 3 applicants who test positive will be falsely identified as drug users, and 1 out of 5 applicants who test positive will be falsely identified as drug users in Case 2. In the population of applicants with low drug usage rates (Case 3), nearly 9 out of 10 positive test results will be erroneous.

GUIDELINES FOR DECREASING THE FALSE ACCUSATION RATE

In general, the false accusation rate will decrease for each additional confirmation of the positive specimens. Therefore, the false accusation rate will be the highest if only a screening test is conducted, will be lower if a confirmation test is conducted of the specimens that screened positive, and will be lower still if a second confirmation test is conducted on the specimens that were positive on the first confirmation. Thus, if a firm establishes the maximum false accusation rate that it is willing to accept, then it is possible to determine, in advance of any actual testing, how many times specimens would need to be tested in order to achieve an actual false accusation rate that is lower than that desired maximum rate. The process is described and illustrated in this section.

Suppose, for example, that a firm wants no more than one falsely accused job candidate out of every 100 identified as positive by the testing process, which represents a maximum false accusation rate of 0.01. For the drugs involved, the firm's laboratory has a false positive rate of 0.1 and a false negative rate of 0.2 for its screening tests. On its confirmation testing, the lab has a false positive rate of 0.001 and a false negative rate of 0.1. Using data from the firm's local business council for its industry, it expects 12 percent of the job candidates tested to have drugs in their specimens.

By performing the following sequence of steps, the firm can determine in advance of any actual testing whether it will need to conduct one or more confirmations in order to achieve its desired false accusation rate. Once these steps are performed, then the firm can be sure that, in the actual tests of its job applicants, its desired false accusation rate will not be exceeded.

Step 1: Determine the maximum false accusation rate deemed acceptable. This rate could be set at any rate desired, except zero which would be impossible to obtain. In order to avoid rejecting otherwise-qualified employees, the rate should be fairly low.

In the hypothetical case described previously, the business involved is willing to accept a false positive drug test result from no more than one out of every 100 positive specimens reported. That is, the business is willing to accept a false accusation rate of 0.01.

Step 2: Determine the false positive and false negative rates for the laboratory being utilized. Whether these rates are provided by the laboratory itself or are based upon independent studies, they should be estimated using blind proficiency testing, to assure that the results are representative of typical testing processes. These rates should be obtained for screening tests only and for the confirmation tests only. If the laboratory is unable or unwilling to provide acceptable evidence of these rates, it should not be used.

In our hypothetical case we know that for screening tests the false positive rate is 0.1 and the false negative rate is 0.2, while for the confirmation tests the false positive rate is 0.001 and the false negative rate is 0.1.

Step 3: Estimate the proportion of the target group of specimens that will truly contain drugs (the drug presence rate). Different proportions would be expected in different situations, as discussed earlier in the section on drug usage rates. For example, for many professionals and police, the rate would be expected to be about 1 percent, and for retail employees the rate would be about 11 percent. A firm could get estimates from the sources we cited earlier, or check with their industry association or local chamber of commerce. In those cases where several different drug-use rates would be applicable, then, to be conservative, the lowest of the rates should be the one chosen.

For our hypothetical case, the firm estimates that 12 percent of the job candidates tested will have drugs in their specimens.

Step 4: Based on the screening test accuracy rates and the expected drug presence rate, calculate the false accusation rate for the group in question. To calculate this false accusation rate, use the drug presence rate from Step 3, and the false positive and false negative rates for screening testing from Step 2. If the false accusation rate is less than or equal to the desired rate (from Step 1), then the process ends and positive test results from the screening test would provide acceptable evidence of drug usage. Then, only a screening test would need to be conducted on job applicants, with any applicant specimen testing positive being assumed to contain drugs. If the false accusation rate is greater than desired, however, then proceed to Step 5.

For our hypothetical case, as illustrated in Table 2, in column four we would use 0.12 for Drugs and 0.88 for No Drugs. In column five we would enter 0.8 for Drugs (1- false negative rate) and 0.1 for No Drugs. Column six figures are the products of the data in columns four and five, and the sum of the two products (0.096 for Drugs, 0.088 for No Drugs, and 0.184 as the sum of these two products). The sum of the two products is the probability of a positive test result. Column seven figures are the proportions of Drugs and No Drugs from the previous column (0.096/0.184 = 0.522 and 0.088/0.184 = 0.478). Thus, the false accusation rate (that is, the proportion of the positive reports that come from drug-free specimens) is 0.478, much greater than the desired rate of 0.01 (from Step 1), so we must proceed to step 5.

Step 5: Estimate the proportion of the remaining specimens that truly contains drugs (the drug presence rate). Recall that the target group of specimens at this stage consists of only those that tested positive in the preceding test, including both true positives and false positives, although, of course, we do not know which is which. The most accurate estimate of the proportion of those specimens containing drugs is the complement of the false accusation rate (1 - false accusation rate) from the preceding test.

For our hypothetical case, we can get these rates directly from column seven for the Screening tests in Table 2 (specifically, 0.522 for the proportion containing drugs and .478 for the proportion not containing drugs, which we place in the appropriate rows of column four for Confirmation 1 (in Table 2).

Table 2
Determining Number of Re-Tests to Obtain Desired Maximum False Accusation Rate

Type of Test	State of Nature	State of Nature Notation S_j	Initial Probability $P(S_j)$	Conditional Probability Given S_j $P(+\|S_j)$	Probability of Positive Result Given S_j $P(+\|S_j)^* P(S_j)$	Revised Probability for State of Nature $P(S_j\|+)$
Screen	Drugs	S_1	0.12	0.80	0.096	0.522
	No Drugs	S_2	0.88	0.1	0.088	0.478
			1.00		P(+) = 0.184	1.000
Confirmation 1	Drugs	S_1	0.522	0.9	0.4698	0.999
	No Drugs	S_2	0.478	0.001	0.0005	0.001
			1.00		P(+) =0.4703	1.000

Step 6: Conduct a confirmation test on the remaining specimens, and calculate a revised false accusation rate for the group. For the confirmation test, use the false positive rate and the complement of the false negative rate for confirmation testing (which are identified in Step 2). If the revised false accusation rate (from Step 6) is less than or equal to the desired rate (from Step 1), then the process ends and positive test results provide credible evidence of drug usage with one screening test and one confirmation test. If the revised false accusation rate still is greater than desired, then go back to Step 5 with data related to those specimens that tested positive in Step 6.

For our hypothetical case, we enter in column five the complement of the false negative rate (0.9) and the false positive rate (0.001) for confirmation tests. After performing the remaining calculations, it can be seen that the revised false accusation rate for our hypothetical case is 0.001, or 1 false accusation out of every 1000 positive test results, which is far less than the firm's desired maximum of 1 out of 100. So, in this case, we know that our results will be sufficiently accurate with one screening test followed by one confirmation test, and the firm should instruct its lab to perform one confirmation on any specimens that screen positive, and report as positive only those specimens that are positive on the confirmation test. If however the revised false accusation rate had still been greater than 0.01, a second confirmation test would need to be conducted, again repeating steps 5 and 6 using data from step 6 of the first confirmation. If an acceptable false accusation rate were obtained after the second confirmation, then the firm would instruct its lab to confirm any specimens that screened positive, to reconfirm any specimens that were positive on the first confirmation, and report as positive only those specimens that tested positive on the second confirmation.

Carefully note that once a firm sets its maximum acceptable false accusation rate, the determination of the number of confirmations needed (if any) will be made before any tests are actually conducted on job candidates, and the laboratory simply will be notified of the required number of confirmations to be conducted on any specimens that test positive.

CONCLUSIONS AND IMPLICATIONS FOR SMALL BUSINESSES

The abuse of drugs by the nation's workers in both small and large businesses is a serious problem that must be addressed on many fronts. In the proper circumstances, urine testing is a valuable weapon in deterring drug use. However, as illustrated in this paper, allegedly-accurate tests for abused drugs can be inaccurate to a disturbingly high degree, under circumstances likely to be present in many small business settings.

Moreover, note that the proportion of people falsely accused increases when a lower percentage of the population being tested is truly on drugs. Thus, positive results of pre-employment tests conducted in environments where low drug usage rates could be expected (for example, tests of applicants for child care and computer programming jobs) should be viewed with more skepticism than positive results in other environments (such as the construction industry).

When testing job applicants, personal and economic costs far in excess of any potential benefits may occur if a high proportion of positive tests come from specimens that do not contain drugs. This potential problem can be avoided, however, by use of the procedure that we have suggested, which will keep the false accusation rate at or below some predetermined level.

This analysis has focused on the personal and economic costs associated with denying employment on the basis of faulty test results. However, there is another important cost of faulty testing processes, and another important group that can be affected by faulty testing. The other cost is the legal cost, and the other group is current employees.

In most instances, job applicants have considerably less legal protection than current employees. For example, state law in some states requires that drug tests of current employees include confirmation processes, whereas confirmation processes are not required for applicants. Similarly, in many instances, union contracts require confirmation testing of current employees. Moreover, applicants typically are not informed as to the reason for non-hire, whereas current employees have more legal recourse in the case of drug testing. While beyond the scope of this paper, legal issues related to drug testing range from the need to satisfy Federally-mandated scientific standards regarding random testing (Gleason and Barnum, 1993), to issues related to tort liability (Lockard, 1996).

Therefore, although we have limited our discussion to pre-employment drug testing, the same potential problems exist for testing of current employees. For current employees, the potential personal, economic and legal costs and obligations are substantially greater than for job applicants, so it is even more important that a procedure such as the one discussed herein be used to avoid inordinate false accusation rates, and that an even lower maximum false accusation rate be set for current employees than for job applicants.

Finally, there is the potential that faulty drug tests may lead to claims of racial bias. A survey in Georgia indicated that firms that employ a large number of blacks are more likely to test job applicants for drugs, and are less likely to satisfy NIDA guidelines for confirmation testing (Lockard, 1996; Sorohan, 1994).

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