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Pressured Into Deception: Using General Strain Theory as a Framework for Testing the Validity of Self-Reported Drug Use

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A Thesis Submitted to The Graduate School at the University of Missouri – St. Louis in partial fulfillment of the requirements for the degree Master of Arts in Criminology and Criminal Justice

May 2011

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Abstract

Determining the accuracy of self-reported drug use is important for criminal justice professionals so that they are better able to provide proper treatment referrals to those in the criminal justice system who may need substance abuse help (Rosay et al., 2007). However, self-reports, especially those of drug users, are not always accurate (Harrison, 1997). Drug use is a highly sensitive topic and disclosure of such behavior could lead to negative repercussions for the individual within the criminal justice system as well as lead to further stigmatization of the individual outside the system (Golub et al., 2002; Harrell, 1997). The current study uses data from the 2003 Arrestee Drug Abuse Monitoring (ADAM) survey to examine the accuracy of self-reported drug use across seven different types of drugs to determine if the anticipated strain of admitting to the use of drugs, compounded by respondents' current levels of strain, are strong enough to inhibit individuals from accurately reporting drug use. Binomial conditional logistic regression models with fixed effects and robust standard errors were used to conclude that experiencing strain reduces the likelihood of accurately reporting drug use. The current study expands the current literature on Agnew's general strain theory to include purposeful deception as a deviant coping mechanism used in response to strain. The results of the current study may help criminal justice professionals more accurately identify active substance abusers who may be less than truthful about their drug use. Implications from this study suggest that it may be useful to incorporate strain-related variables into the risk and needs assessment measures that criminal justice professionals use to better guide treatment referrals.

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Chapter One

Introduction

"Never have I lied in my own interest; but often I have lied through shame in order to draw myself from embarrassment..." —Jean-Jacques Rousseau, *Reveries of the Solitary Walker*

Accurate self-reported drug use (i.e., when an individual truthfully admits to illicit/licit substance use) is an important issue for criminal justice professionals so that they are better able to provide proper treatment referrals to those in the criminal justice system who may need substance abuse help (Falk et al., 1992, Magura et al., 1987; Rosay et al., 2007). However, self-reports, especially those of drug users, are not always accurate (Harrison, 1997). Drug use is a highly sensitive topic and disclosure of such behavior could lead to negative repercussions for the individual within the criminal justice system as well as lead to further stigmatization of the individual (e.g., as a drug user) outside the system (Golub et al., 2002; Harrell, 1997). This study seeks to reach a more nuanced understanding of the predictors of accurate self-reported drug use. Such information may better inform criminal justice workers so that they are more readily able to identify users who might be less than truthful about their drug use. The current study examines the accuracy of self-reported drug use across multiple types of drugs to determine whether strain is a common predictor of inaccurate self-reports.

The predictors of accurate self-reported drug use vary dramatically across the type of populations and drugs being studied (Katz et al., 1997; Lu et al., 2001; Magura and

King, 1996; McElrath et al., 1995; Rosay et al., 2007; Sloan et al., 2004). Magura and King (1996) found that offenders in the criminal justice system tended to less accurately report drug use compared to other populations not involved with the criminal justice system, such as those in drug treatment programs. Predictors of accurate self-reported drug use also vary by the type of drug the individual is using. For example, predictors of accurate self-reported cocaine use differ from the predictors of accurate self-reported heroin use or marijuana use (Gray and Wish, 1999; Katz et al., 1997; Sloan et al., 2004). Rosay and colleagues (2007) argue that most other predictors of accurate self-reported drug use are inconclusive due to the operational definition of accurate self-reported drug use, which varies across studies. Some studies only include in their sample those who test positive for a drug, whereas other studies use the entire sample, including those who tested negative for all types of drugs (Rosay et al., 2007). Retention of those who tested positive and those who tested negative in the sample skews the results toward those who tested negative, since those who test negative are more likely to accurately report their drug use (Rosay et al., 2007). Therefore, when examining predictors of self-reported drug use, it is important that studies only include respondents who test positive for drug use in a subsequent urinalysis.

Prior literature on the accuracy of self-reported drug use and the predictors of accurate self-reported drug use can be categorized into two separate frameworks intentional and non-intentional inaccuracies. These frameworks are useful for documenting the intent of the respondent. Past literature that attributes discrepancies between urinalysis tests and self-reported drug use as accidental are classified here as non-intentional inaccuracies. Research argues these discrepancies are due to cognitive

impairments of the respondent (i.e., unaware of the date a drug was consumed) or validity issues with the urinalysis tests (Falck et al., 1992; Golub et al., 2005; Magura et al., 1987). This framework helps explain why some individuals' self reports are inaccurate; however, this framework fails to explain why inaccuracies occur across different types of samples (e.g., treatment versus criminal justice) and across the different types of drugs used by an individual (e.g., marijuana versus cocaine). Past literature that uses intentional deception as an explanation for inaccurate self-reported drug use relies on the social desirability thesis (Sloan et al., 2004). This thesis is based on the idea that the more socially stigmatized a behavior is perceived to be by a respondent, the more likely it will be that the person will deny engaging in that particular behavior (Edwards, 1953). Past research has suggested that marijuana use is often perceived to be less stigmatized and therefore, more accurately reported, than drugs that are perceived to be more stigmatized like cocaine or heroin (Preston, 2006; Sloan et al., 2004). Therefore, the social desirability thesis helps explain the accuracy of self-reported drug use but fails to adequately explain the predictors of inaccurate self-reports.

The current study attributes discrepancies between urinalysis test results and selfreported drug use to intentional inaccuracies, but differs from prior studies in that it uses Agnew's (1985) general strain theory as a framework to explain the predictors of accurate self-reported drug use. Strain is most often defined as unfavorable events or situations that lead individuals to cope through illegal/deviant means (Agnew, 2006; Brezina, 1996). Using this framework, the strain an individual experiences may increase if he or she admits to drug use because of perceived social stereotypes that may lead to further stigmatization of the individual during an arguably stressful time in their life (i.e.,

being in jail). By admitting to drug use, individuals may also be subjected to additional criminal charges or further criminal investigations; both of which are anticipated strains.

Using the 2003 Arrestee Drug Abuse Monitoring (ADAM) data, the current study examines the congruence rates between self-reported drug use and subsequent urinalysis test results, in addition to the predictors of accurate self-reported drug use. ADAM is a probability-based survey designed to collect reliable estimates of drug use behavior and related problems in the population of individuals currently in the custody of local jails in 39 different cities nationwide. The sample in the current study consists of males in the criminal justice system, who have tested positive for one or more of the following drugs: cocaine, opiates, methamphetamine, marijuana, benzodiazepines, methadone, and/or alcohol. For each drug category, the main hypothesis is that those who experience greater levels of strain will be less likely to accurately report drug use. It is argued that admitting to drug use would cause additional strain above and beyond the individual's current level of strain, and thus, may result in intentional deception as a coping mechanism.

Limitations of the current study include generalizability issues and the operationalization of the various types of strain. The current study's findings will not be generalizable to the population of those in jails nationwide or to those in other criminal justice facilities, since the ADAM sample is not representative of all individual offenders in the U.S. Another limitation is that all measures of strain in the current study are objective instead of subjective. Objective strains are events or situations that are typically disliked by everyone who would experience them (Froggio and Agnew, 2007). On the other hand, subjective strains are events or circumstances experienced by an

individual who then rates the events or circumstances as stressful (Froggio and Agnew, 2007). Therefore, not all objective strains may be evaluated by the respondent as stressful events and these events may not be equally stressful for all individuals in the study. Nonetheless, it is important to take the first step toward determining whether there is a common predictor (strain) of inaccurate self-reported drug use so that professionals in the criminal justice system may more accurately identify and assist those with a substance abuse addiction.

In the following chapters, this study will explore whether strain is a common predictor of inaccurate self-reported drug use. Specifically, chapter two includes a detailed description of the prior literature on the predictors of accurate self reported drug use and includes a discussion of the relevancy of Agnew's general strain theory as an explanation for inaccurate self-reports. Chapter three includes a thorough description of the ADAM data and statistical methods used in this study. Chapter four presents results of the analyses. Chapter five offers a discussion of the findings and highlights possible contributions to the strain and self-report literature. Chapter five also concludes this study with a brief discussion of its limitations and possible implications for future research.

Chapter Two

Literature Review

Self-reported drug use was once believed to be highly accurate (Amsel et al., 1976; Ball, 1976; Bonito et al., 1976; Cark and Tifft, 1966; Stacy et al., 1985; Stephens, 1972). Past comparison criteria used to validate self-reported drug use in these earlier studies were polygraph tests (Clark and Tifft, 1966), peer reports (Aiken and Losciuto, 1985; Stacy et al., 1985; Stephens, 1972), police reports (Bonito et al., 1976), or thin layer chromatography urinalysis tests¹ (Amsel et al., 1976; Ball, 1976; Page et al., 1977). However, more recent studies have cast doubt on these techniques by using more precise urinalysis test procedures and more refined study methodologies: such as only including those who test positive for substance use (Magura et al., 1987; Rosay et al., 2007). This has led to a decrease in the presumed confidence of self-reported drug use (Magura et al., 1987; Maisto et al., 1990; Rosay et al., 2007).

The accuracy of self-reported drug use is dependent on the base rates of those included in the sample (Rosay et al., 2007). The accuracy of self-reported drug use decreases with the number of respondents who test positive for a drug (Rosay et al., 2007). This is because respondents who test negative for drugs in a urinalysis will typically accurately deny use of an illicit substance (Rosay et al., 2007). The inclusion of non-users, therefore, skews the results toward those who do not use illicit substances. According to Rosay and colleagues (2007), the only viable way to overcome this

¹ Earlier comparison studies used Thin Layer Chromatography (TLC) as a comparison criterion; however, TLC has been shown to be inaccurate compared to Gas Chromatography/Mass Spectrometry (GC/MS) (Visher, 1991). In a study of known positive drug specimens, TLC was only able to accurately identify 48 percent of the positive marijuana samples, 11 percent of the cocaine samples, and 8 percent of the opiate samples (Visher, 1991).

limitation is to eliminate those respondents who test negative for all illicit substances so that the rate of accurately reporting drug use is based solely on respondents who test positive for illicit substances. If non-users are included in the sample, then differences across drug types and samples would reflect the differences in the rate of testing negative instead of the differences in accurate reporting.

The reliability of self-reported drug use is not nearly as questionable as its validity (Golub et al., 2005; Rosenfeld and Decker, 1992). Prior literature has concluded that the disparity between self-reported drug use and actual use within a criminal justice sample is reliable across year, city, and type of drug (Golub et al., 2005; Rosenfeld and Decker, 1992). This has allowed researchers to focus more on the predictors of accurate selfreported drug use, although the extant literature is still inconclusive as to the predictors of accurate self-reports. Previous studies often failed to adequately note whether or not those who tested negative were eliminated from the samples or whether over-reporters were combined with under-reporters (Rosay et al., 2007). Even when previous studies clearly defined the base rates of those included in the samples and used criminal justice samples, it remains difficult to reach specific conclusions due to sampling differences across these studies. For example, Lu and colleagues (2001) looked at adult males who tested positive for the use of marijuana, methamphetamine, opiates, and crack-cocaine, whereas Rosay and colleagues (2007) used a sample that consisted of adult males who tested positive for marijuana and cocaine/crack-cocaine. Gray and Wish (1999) examined females who tested positive for cocaine, opiates, and marijuana. Fendrich and Xu (1994) examined male juveniles who tested positive for cocaine, heroin, and marijuana. As a result, it is difficult to determine, with confidence, the predictors of

accurate self-reported drug use because of the differences in the samples examined in past studies.

Two factors that influence the accuracy of self-reported drug use that are constant throughout the prior literature are the type of drug used and whether the sample was drawn from a substance abuse treatment program or from those currently in the custody of the criminal justice system. Looking at the type of drug used, many studies that eliminated non-users from their samples concluded that marijuana is the most accurately reported drug (Fendrich and Xu, 1994; Golub et al., 2002; Kim et al., 2000; Lu et al., 2001; Magura and Kang, 1996; Rosay et al., 2007). Researchers have suggested that this is the case because marijuana is perceived by users to be less stigmatized than other illicit drugs (Lu et al., 2001; Magura and Kang, 1996; Rosay et al., 2007). Therefore, the predictors of self-reported marijuana use should differ from the predictors of self-reports of other types of illicit substances (Lu et al., 2001; Rosay et al., 2007). The other factor that influences the accuracy of self-reported drug use is whether respondents are currently enrolled in substance abuse treatment or are in the custody of the criminal justice system (Magura and Kang, 1996). According to Magura and Kang (1996), samples pulled from the criminal justice system tend to less accurately report drug use than samples drawn from substance abuse treatment programs. The nature of seeking help for substance abuse from a drug treatment program requires an individual to at least indirectly admit to using drugs in order to receive help. In addition, since the individual is seeking help for a substance abuse problem, the individual has little reason to misrepresent his or her recent drug use. On the other hand, once an individual is brought into the criminal justice system, admitting to drug use may bring additional negative consequences (Magura and

Kang, 1996). Therefore, the predictors of self-reported drug use differ depending on if the sample was drawn from those in the criminal justice system or from those in a substance abuse treatment program.

Strong conclusions regarding other predictors of accurate self-reported drug use are difficult to draw due to the differences in the base rates of those included in the sample (e.g., accurately reporting non-users combined with accurately reporting users, non-users eliminated, over-reporters combined with under-reporters); differences in sampling (e.g., substance abuse treatment sample or criminal justice sample), and differences in the drugs examined in the study (e.g., cocaine, opiates, marijuana). For these reasons the body of literature on the predictors of accurate self-reported drug use remains largely inconclusive. The current study addresses these issues by examining a criminal justice sample that excludes those who test negative for an illicit/licit substance. This study also examines seven different drug types to more accurately identify predictors of accurate self-reports for each drug type.

Frameworks Used in Past Studies

Several theoretical frameworks have been used to explain the patterns found among inaccurate self-reported drug use. These frameworks are useful in attempting to understand why certain patterns emerge in accuracy rates of self-reported drug use. Past literature on the accuracy of self-reported drug use can be categorized into studies of either non-intentional or intentional inaccuracies. Both categories refer to the intent of the respondent. Non-intentional inaccuracies are not classified as deception since the respondent did not deliberately try to deceive the interviewer. On the other hand, intentional inaccuracies are deliberate deception by the respondent to disguise recent drug use. Frameworks that have relied on non-intentional inaccuracies have attributed self-reported discrepancies to cognitive impairments of the individual or the validity of the urinalysis test itself. Prior literature that has attributed inaccuracies to deliberate deception by the respondent have used the social desirability thesis to explain why a respondent may try to mislead the interviewer. Past intentional and non-intentional inaccuracy literature fails to adequately explain the discrepancies between self-reported drug use and urinalysis results *and* the predictors of these inaccuracies. The current study attributes inaccuracies to intentional deception and uses Agnew's (2001) general strain theory to better explain the patterns found in the predictors of accurate self-reported drug use.

Non-Intentional Inaccuracy: Test Adequacy

Prior literature has attributed errors in self-reported drug use to the inadequacy of urinalysis testing methods (Golub et al., 2005; Magura et al., 1987). Drug urinalyses are considered positive if the drug's metabolites are found in the urine specimen (Visher, 1991). The accuracy of these tests is determined by the tests' sensitivities and specificities. The sensitivity of the test is its ability to detect an illicit substance in a positive urine specimen (Visher, 1991). A high sensitivity level allows the test to detect low levels of the drug in a urine specimen, while a low sensitivity level may produce false negatives (specimen tests negative but is actually positive) (Visher, 1991). The test's specificity is its ability to discriminate between drug metabolites and foreign metabolites in the urine specimen (Visher, 1991). If the test is unable to discriminate between foreign substances and drug metabolites in the specimen, then false positive findings (the specimen tests positive but is actually negative) may occur (Visher, 1991).

The majority of recent studies of the validity of self-reported drug use have used Enzyme Multiplied Immunoassay Tests (EMIT) instead of Thin Layer Chromatography that was primarily used by earlier self-report drug studies. According to Visher (1991), the false positive rate and the false negative rate for EMIT varies depending on the drug being examined. EMIT has a false positive rate of 2.5% for cocaine, 2.2% for opiates, and 2.1% for marijuana (Visher, 1991). EMIT has a false negative rate of 22.8% for cocaine, 17.9% for opiates, and 29% for marijuana (Visher, 1991). Therefore, the sensitivity of EMIT is poor while the specificity of EMIT is high.

According to Golub and colleagues (2005), EMIT's inability to correctly identify those who test positive for drugs is the major reason for discrepancies between selfreported drug use and the results from the urinalyses. However, this discrepancy stems from respondents who over-report drug use in the sample, not those under-reporting drug use since EMIT's specificity level is high (few false positives were found in the sample). When nonusers are eliminated from the sample, only 2.1% to 2.5% of the sample remains misclassified. Therefore, this framework fails to correctly specify why large inaccuracies occur between self-reported drug use and results from the specimen tests.

Non-Intentional Inaccuracy: Cognitive Frameworks

Past studies that used cognitive frameworks concluded that inaccuracies in selfreported drug use were often the result of memory errors (Harrell, 1997; Harrison, 1995; Katz et al., 1997; Nelson et al., 1998). According to Harrell (1997), drug users may have difficulty remembering the exact times or dates that they consumed a drug, in part due to the physiological effects of the drug on the mind of its users. Also, the more drugs an individual uses, the more difficulty the individual will have in remembering and reporting when he or she used each drug (Harrell, 1997). For example, some drug users might believe that they used an illicit substance four days ago, when in reality they used a drug two days ago. These drug users would be under-reporting their drug use by accident instead of deliberately deceiving the interviewer.

Memory errors may also occur if the drug user is unaware of the particular drug(s) used (Harrison, 1995; Magura et al., 1987; Nelson et al., 1998). Drug users may think they are using a particular drug when they are actually using another illicit substance. This would result in the respondent over-reporting one type of drug and under-reporting another type of drug. Individuals may also be unaware that they are consuming a drug if it is laced with other drugs. For example, an individual may believe he or she smoked marijuana rolled in a cigar; however, the cigar may in fact contain both marijuana and cocaine. This would result in the respondent under-reporting cocaine use. Cognitive frameworks may explain some of the discrepancies between self-reported drug use and urinalysis results, but these frameworks fail to explain why the discrepancies change across drug type and population.

Intentional Inaccuracies: Social Desirability Thesis

In recent years researchers have relied on the social desirability thesis to explain discrepancies between self-reported drug use and urinalysis results. According to

Edwards (1953), the social desirability thesis may best be understood as a continuum ranging from actions that an individual perceives to be socially desirable, and thus less stigmatized, to behaviors one would perceive as socially undesirable, and thus more stigmatized. The more socially desirable the respondent perceives the behavior to be, the more likely the respondent will endorse or acknowledge the behavior. Conversely, the more socially undesirable the respondent perceives the behavior to be, the more socially undesirable the respondent perceives the behavior to be, the more socially undesirable the respondent perceives the behavior to be, the more likely the respondent will deny the behavior in question. Drug use can be a highly stigmatized behavior because the criminal justice system may impart a formal label on the user. For example, this label might cause later stigmatization of the individual as the individual attempts to find and maintain employment (Pager, 2003).

Support for the social desirability thesis has been found in recent studies that show marijuana is more accurately reported than other illicit substances (Harrison 1995; Lu et al., 2001; Sloan et al., 2004). This has been attributed to the idea that admitting to marijuana use carries less of a stigma than admitting to use of other illicit drugs (Falck et al., 1992; Harrison, 1995; Lu et al., 2001; Rosay et al., 2007; Sloan et al., 2004). This framework describes why certain drugs are more accurately reported than others, but fails to identify which predictors are associated with inaccurate self-reports. This occurs since socially undesirable/desirable behaviors differ between subcultures (Edwards, 1957). Therefore, without asking the respondent whether he or she perceives the behavior as desirable or not, the thesis is unable to determine which personal characteristics lead to more accurate self-reported drug use.

Intentional Inaccuracies: Agnew's General Strain Theory

Past literature has yet to utilize Agnew's general strain theory (2001) to explain the inaccuracies of self-reported drug use or the predictors of these self-reports. However, exploratory studies on the accuracy of self-reports have reached similar conclusions that resemble the various parts of general strain theory. One of these findings is that the respondent's perceived fear of negative consequences or reprisals inhibits the respondent from accurately reporting his or her drug use (Falck, 1992; Gray and Wish, 1999; Kim et al., 2000; Rosay et al., 2007). The fear of consequences or reprisals can be viewed as an example of an anticipated strain. Therefore, it appears there may be support for general strain theory in explaining the inaccuracies of self-reported drug use, despite the theory not having been formally introduced or expanded upon in prior self-reported drug use literature.

Agnew (2006) defines strain as unfavorable life events or situations that lead a person to cope through either legal or illegal/deviant means. Strains can be either objective or subjective. Objective strains are events or conditions that are generally disliked by most people, whereas subjective strains are events or circumstances that are disliked by the individual experiencing the strain (Agnew, 2001). Some objective strains may also be subjective strains, however, this can be difficult to ascertain unless the individual is specifically questioned about the event or situation (Agnew, 2001; Froggio and Agnew, 2006). According to Agnew (2001), subjective strains should be more closely linked to deviant coping mechanisms than objective strains. The current study focuses on objective strain because past literature has also concluded that objective strain is correlated with illegal coping mechanisms (Agnew and White, 1992; Broidy, 2001).

According to Agnew (2001), the most common types of strain include situations in which the individual loses something of value (loss of a positive stimulus), the individual is treated in a negative manner (presentation of a negative stimulus), or the individual is unable to obtain specific goals (goal blockage) (Agnew, 1992). These types of strain are expected to lead to negative emotional states such as anger, depression, and fear (Agnew, 2001). These strong emotional states create pressure for corrective action through deviant means (Agnew, 2001). These pressures reduce the individual's ability to cope in a legal manner and reduce the perceived costs of coping through deviant means, thus increasing the propensity to engage in illegal or deviant behaviors (Agnew, 2006).

Some individuals have a variety of coping mechanisms available to them that allow them to effectively reduce the effects of stressful events without resorting to deviant coping strategies (Angew, 2006; Thoits, 1983). However, individuals who have been unsuccessful at coping in past stressful situations may begin to view themselves as having less ability to deal with strain, which subsequently decreases their feelings of personal control over their lives (Abramson et al., 1978; Kaplan, 1980). This may lead individuals to believe that they are incapable of coping with stressful situations in a legal manner and may create the pressure necessary for the individual to cope in an illegal or deviant way (Agnew, 2006).

The cost of criminal coping is strongly dependent on the individual's social environment (Agnew, 2006). Individuals more likely to cope through deviant methods often reside in environments where there are few repercussions for criminal or deviant behavior (Agnew, 2006). These individuals may have become accustomed to handling stressful situations with deviant behaviors. The propensity to engage in deviant behavior

can also depend on the individual's personality traits (Agnew, 2006). Individuals who commonly experience strong emotions are more likely to engage in deviant coping strategies than individuals who do not easily get upset (Agnew, 2006). Those who have experienced less severe emotions due to strain are less likely to believe that coping through deviant means is an appropriate response to distress (Agnew, 2006).

Agnew (2001) argues that strains an individual perceives to be unjust, high in magnitude, are associated with low social control, or that create some pressure to engage in criminal coping are the most likely to lead to deviant behavior as a coping mechanism. According to Agnew (2001), all four of these factors are equally influential in leading an individual to cope in a deviant way. Similarly, the lack of any of these four characteristics substantially reduces the likelihood that the individual will cope through deviant methods. According to Agnew (2001), unjust strains are likely to elicit strong emotions like anger which are more likely to lead to deviant coping mechanisms. The magnitude of a strain is dependent on the degree, duration, recency, and importance of the strain. Both the accumulation and clustering of stressful events may overtax the individual's pro-social coping mechanisms (Agnew, 1992; Linsky and Straus, 1986; Thoits, 1983). Therefore, when multiple stressful situations occur, especially within a short period of time, the individual's pro-social coping mechanisms may become exhausted, pushing the individual to cope in a deviant manner (Agnew, 2006; Thoits, 1983). Strains that are associated with low social control often lead to deviant coping responses in the individual due to the perceived reduction of the costs of crime and the lack of social support (Agnew, 2001). Certain strains influence the individual's available

coping responses, which creates the incentive and pressure necessary to respond to the stressor in a deviant manner (Agnew, 2001).

According to Agnew (2006), anticipated strains also generate the emotions necessary for the predisposition of delinquency. Anticipated strains occur when the individual anticipates strain in the near future or anticipates a current strain continuing into the future (Agnew, 2002). Thoits (1983) argues that anticipated strains can be as distressing as unexpected strains. As a result of these anticipated strains, individuals often adopt delinquent behaviors in order to prevent the strain from occurring (Angew, 2002; Agnew, 2006; Brezina, 1996).

According to past literature, stressful situations may interact with other stressful situations (Agnew, 1992; Thoits, 1983). For example, an individual who experiences a stressful event may be subject to more distress when a second stressful situation occurs (Thoits, 1983). For such an individual, deviant coping mechanisms may allow the individual the ability to reduce or even escape from the strain(s) that created the negative emotions (Agnew, 2006).

Admitting to using an illicit substance could lead to stigmatization of the individual inside the criminal justice system and in society in general. Inside the criminal justice system, respondents may receive additional felony charges or be subject to investigations that would not have occurred if he or she did not admit to drug use. Therefore, the fear of an additional charge may be both the presentation of a negative stimulus (i.e., an additional criminal charge) and the removal of a positive stimulus (i.e., additional loss of freedom) if an individual believes he or she will be given a longer jail sentence or harsher punishment. The label of convicted drug user may be a goal

blockage if the individual believes it will become harder for the individual to secure subsequent employment due to this negative label.

According to strain theory, those who experience greater levels of strain are more likely to experience strong emotional states that in turn may increase delinquency, or in this case, intentional deception. The current study will look at the accuracy of selfreported drug use in a sample of individuals who are being held in jail at the time of the interview and urinalysis test. The cost of criminal coping for these individuals should be low due to their immediate social environment (i.e., jail). These individuals are also expected to experience strong emotional states due to the numerous stressors inherent in the jail environment, such as overcrowding, unsanitary living conditions, harassment, and idleness (Sheldon, 2010). It is predicted that admitting to the use of an illicit or licit substance would further increase the individual's level of strain above and beyond the strain experienced by being in custody. If the respondent's current level of strain is already viewed as unjust or high in magnitude then the anticipated strain of admitting to drug use may increase the individual's already high level of strain, which would reduce the effectiveness of the individual's pro-social coping mechanisms. For each separate drug category, it is predicted that those who experience increased levels of strain due to their life circumstances, will be less likely to accurately report drug use.

Over the past several decades, the accuracy of self-reported drug use has been examined through many different frameworks that included intentional and nonintentional inaccuracies. However, these frameworks failed to fully explain the disparity found between self-reported drug use and actual drug use. The current study extends the literature on accurate self-reported drug use by incorporating a contemporary theoretical

model, general strain theory, to examine the predictors of accurate self-reported drug use. In addition, the current study expands on the prior literature by examining the predictors of inaccurate self-reports of seven different illicit/licit substances: cocaine, opiate, methamphetamines, marijuana, benzodiazepines, methadone, and alcohol.

Chapter Three

Data and Methods

To examine if strain-related variables are predictors of inaccurate self-reported drug use, this study combines individual level data from the 2003 Arrestee Drug Abuse Monitoring (ADAM) program² and community level data from the 2000 U.S. Census. The ADAM data come from interviews of males incarcerated in jail in 39 cities across the U.S. ³ Community level data come from the Summary Tape File 3 in the 2000 U.S. Census and include city- and county-level data. This chapter describes the data, measures, and methods used in the current study to examine the relationship between strain and inaccurate self-reported drug use in a jail-incarcerated population of males.

Sample

In this study, the ADAM data capture self-reported drug use and several indicators of strain. ADAM is a probability-based survey designed to collect reliable estimates of drug use behavior and related problems in a population of arrested individuals within a given catchment area of local jails. Survey participants were drawn from arrest logs maintained by local law enforcement agencies. ADAM protocol is to record arrest information on all individuals entering the jail, even if individuals were immediately released from jail or if they refused to participate in the survey. ADAM data collection goals were to represent all arrestees from all days of the week and all times of

² ICPSR study number 4020.

³ Please refer to Appendix A for the list of cities in the 2003 ADAM data.

the day in a particular area. This was accomplished by collecting the ADAM data during a two-week time period, four times a year for each of the 39 sites. Approximately 31% of the sample were not available to be interviewed because of being released quickly after arrest. Of those arrested and in jail, approximately 84% agreed to be interviewed. Of those interviewed, 93% of respondents provided a urine specimen for the urinalysis. Those that were unavailable for the current study were statistically different from the current sample based on severity of offense, charge of offense, race, and age. However, the statistical difference primarily resulted from the large sample size. Similar differences existed between those who submitted to a urinalysis and those who refused or failed to provide a proper urinalysis sample. This study includes only those respondents who answered the drug use questions and provided a urine specimen.

The ADAM survey uses the EMIT method to test urine specimens for the presence of cocaine, opiates, amphetamines, marijuana, benzodiazepines, methadone, alcohol, propoxyphene, barbiturates, and phencyclidine (PCP). All specimens that test positive for amphetamines are then retested using the more precise gas chromatography/mass spectrometry (GC/MS) method to determine if the sample is positive for methamphetamines. The current study includes the following substances in its analyses: cocaine, opiates, methamphetamine, marijuana, benzodiazepines, methadone, and alcohol. Not all substances are included in the current study because of the length of time certain substances can be detected in a urine specimen and the total number of respondents testing positive for the substance. Substances with a low rate of prevalence in the data were excluded. For example, the barbiturate model was not

incorporated into the current study since it would have only included 96 respondents. ADAM data collectors obtained a urinalysis from each respondent and also collected selfreported drug use information for all substances. This information allows for comparisons between self-reported drug use and the corresponding urinalysis test results to determine the accuracy of self-reported drug use. The ADAM data collectors also obtained several individual-level indicators of strain such as homelessness, minority status, educational underachievement, and unemployment. Therefore, these data permit examination of the relationship between several individual-level indicators of strain and inaccurate self-reported drug use.

The 2000 U.S. Census was incorporated into the current dataset to examine the effect of neighborhood-level measures of strain (combined into a "neighborhood disadvantage" scale) on inaccurate self-reported drug use. Census data were pulled from Summary Tape File 3 that included information on the city- and county-level unemployment rate, percent living below the poverty level, percent of female headed households, and percent of households receiving public assistance.

Dependent Variables

The current study examines predictors of accurate self-reported drug use across seven different types of drugs: cocaine, opiates, methamphetamine, marijuana, benzodiazepines, methadone, and alcohol. Separate regression models were created for each of the seven drug types. The accuracy rates for reporting each drug were created by comparing respondents' urinalysis test results with corresponding self-reports. For each model, only respondents who tested *positive* for the reported drug are included in the analysis to ensure results are not skewed toward respondents who tested negative for the same drug. Please refer to Table 1 for the coding scheme.

Cocaine

The urinalysis test in the ADAM survey is unable to differentiate between cocaine and crack-cocaine. Therefore, self-reported cocaine use in the past 72 hours is combined with self-reported crack-cocaine use in the past 72 hours and was made into one dichotomous variable representing use or nonuse. The new combined self-reported cocaine variable was then compared to positive cocaine test results. Cocaine and crackcocaine have a similar detection window of two to three days in a urine specimen (Hunt and Rhodes, 2001). Since the self-reported cocaine measure is equal to the detection window of cocaine, no error should be introduced into the model due to unequal time frames.

Opiates

Opiate use can be detected up to three days after use in a urinalysis (Hunt and Rhodes, 2001). Therefore, self-reported opiate, heroin, painkillers, and other opiatebased medications in the past 72 hours are combined into one measure called "opiate use." Included in the combined variable are responses to the question "what other type of drug have you used in the past 72 hours" that were manually examined for any opiatebased medication use. These included the substances: Demerol, morphine, Oxycontin, Loratab, codeine, Hydrocodone, Tylenol 3, and Tylenol 4. The combined self-reported

Table 1. Coding	g Scheme of Depen	dent. Independent.	, and Control Variables

Coding Sc	cheme	
Dependen	t Variables:	
1	Cocaine	Inaccurately Report Cocaine Use $= 0$
		Accurately Report Cocaine Use =1
	Opiates	Inaccurately Report Opiate Use $= 0$
		Accurately Report Opiate Use =1
	Methamphetamine	Inaccurately Report Methamphetamine $Use = 0$
		Accurately Report Methamphetamine Use $= 1$
	Marijuana	Inaccurately Report Marijuana Use $= 0$
		Accurately Report Marijuana Use $= 1$
	Benzodiazepines	Inaccurately Report Benzodiazepine Use $= 0$
		Accurately Report Benzodiazepine Use = 1
	Methadone	Inaccurately Report Methadone Use $= 0$
		Accurately Report Methadone Use $= 1$
	Alcohol	Inaccurately Report Alcohol Use $= 0$
		Accurately Report Alcohol Use $= 1$
Independe	ent Variables:	
1	Relative Disadvantage	Continuous Level Variable, Mean-Centered 0 for Each DV
	Homeless	Not Homeless $=0$
		Homeless = 1
	Minority Status	Separate Dummy Variables for Each Category
	White	White is the Reference Category
	Black	
	Hispanic	
	Other Minority	
	Educational Underachievement	Coded as an Ordinal Level Variable
	College Education	
	High School Diploma or GED	
	No High School Diploma or GED	
	C	
	Unemployed	Separate Dummy Variables for Each Category
	Employed	Employed is the Reference Category
	Unemployed	
	Other	
	Offense Severity	Separate Dummy Variables for Each Category
	Felony	Felony is the Reference Category
	Misdemeanor	
	Traffic/Local Ordinance	
	Offense Charge	Separate Dummy Variables for Each Category
	Violent	Violent Charge is the Reference Category
	Drug	
	Property	
	Other	
	Never Been Arrested Before	Was Previously Arrested $= 0$
		Never Been Arrested Before $= 1$
	Never Been to Jail Before	Has Previously Been to $Jail = 0$
		Never Been to Jail Before =1
Control V	ariables:	
Control Vi	Age	Continuous Level Variable, Mean-Centered 0 for Each DV
	Marital Status	Separate Dummy Variables for Each Category
	Married	Married is the Reference Category
	Single	married to the reference category
	Div/Sep/Wid	
	Out-Patient Treatment	Never Been in Out-Patient Treatment $= 0$
	our ration frouthon	Been in Out-Patient Treatment = 1
	Hours Since Arrest	Continuous Level Variable, Mean-Centered 0 for Each DV
	Interviewer Characteristics	Separate Dummy Variables for Each Category
	Same Age As Respondent	Same Age As Respondent is the Reference Category
	Older Than Respondent	sume rige ris respondent is the reference category
	Younger Than Respondent	
	Different Gender Than Respondent	Same Gender as Respondent $= 0$
	Different Genuer Finan Kespondent	Different Gender as Respondent = 1
	Different Page Than Permendent	*
	Different Race Than Respondent	Same Race as Respondent $= 0$
	Quarter	Different Race as Respondent = 1
	Quarter	Separate Dummy Variable for Each Category
	First	First Quarter is the Reference Category
	Second	
	Third	
	Fourth	

"opiate use" variable was then compared to positive opiate test results. No error should be introduced into the opiate model because the combined self-reported opiate use variable uses the same time frame as the urinalysis window of detection for opiates.

Methamphetamine

All urinalysis test results included in the ADAM data that were positive for amphetamines were retested for methamphetamine using the GC/MS method, since the more common EMIT is unable to differentiate between amphetamines and methamphetamine. Methamphetamine is the only drug in the ADAM survey that is confirmed by additional testing of the specimen. Self-reported methamphetamine use in the past 72 hours was then compared to positive methamphetamine test results. Some error will be introduced into the statistical results since methamphetamine use can be detected up to four days after last use of the drug in a urine specimen (Hunt and Rhodes, 2001). Respondents who used methamphetamine four days prior to the survey, but not within the three day time window asked in the survey, will accurately be under-reporting methamphetamine use. Accurately under-reporting methamphetamine use is not deliberate deception since respondents are correctly identifying their drug use, but is a limitation of the current study's inability to match the methamphetamine window of detection with the self-report period.

Marijuana

According to Hunt and Rhodes (2001), infrequent marijuana use can be detected in a urinalysis specimen up to 30 days after use and heavy marijuana use can be detected

well beyond 30 days after last use of the substance. The current study compared selfreported marijuana use in the past 30 days to positive marijuana test results. Some error is expected to be introduced into the current study since heavy users may test positive for marijuana past the 30 day window. However, by definition, heavy use implies that the individual routinely uses marijuana which would be reported by the user within the survey's 30-day window.

Benzodiazepines

Several transformations were made to the self-reported benzodiazepine variable before it was compared to positive benzodiazepine test results. Self-reported benzodiazepine, tranquilizers, and other benzodiazepine-based medications in the past 72 hours were combined into one measure. Included in the combined benzodiazepine variable were responses to the question "what other type of drug have you used in the past 72 hours" that were manually examined for any benzodiazepine-based medication use. These included the following substances: Librium, Valium, Ativan, Xanax, Tranxene, Klonopin, anxiety medication, and sleeping pills. The combined variable was then compared to positive benzodiazepine test results. Some error is expected to be introduced into the model since benzodiazepines can be detected in a urinalysis up to two weeks after last use of the substance (Hunt and Rhodes, 2001). For example, if respondents used benzodiazepines between three and fourteen days before the urinalysis, but not within the three day window of the survey, then the respondents will be accurately under-reporting benzodiazepine use.

Methadone

No data transformations were necessary for self-reported methadone use. Methadone use within the past 72 hours was compared to positive methadone test results. Small amounts of error are expected to be introduced into the study since methadone can be detected in a urinalysis up to four days after last use (Hunt and Rhodes, 2001). Therefore, all respondents who used methadone four days prior to the survey, but not within the three day reporting window of the survey, will be accurately under-reporting methadone use.

Alcohol

No data transformations were necessary for self-reported alcohol use. However, the 2003 ADAM survey data collectors did not question respondents about alcohol consumption in the last three days. Instead, the ADAM survey inquired about selfreported alcohol use within the past 30 days. These responses were compared to positive alcohol tests results. Traces of alcohol can remain present in a urine specimen for up to five days after consumption (Wurst et al., 2005). This means almost all errors due to cognition are eliminated from the model because the window of detection for the urinalysis (five days) is less than the self-reported time frame (thirty days). It is assumed that the anticipated strain of admitting recent use of alcohol is partially eliminated since the respondent is not required to admit recent alcohol consumption.

Independent Variables

According to Agnew's general strain theory (2001, 2006), certain types of strain are more strongly related to deviant behavior since they are generally associated with being unjust, high in magnitude, associated with low social control, or create pressure for criminal coping. The following strain variables were examined in this study: relative neighborhood disadvantage, homelessness, minority status, educational underachievement, and unemployment.

The relative neighborhood disadvantage variable was created by linking the respondents' reported zip codes with data from the 2000 U.S. Census. In addition, each zip code was linked to its respective county, which was also linked to data from the 2000 U.S. Census. Therefore, two scales were created: one for neighborhood disadvantage ($\alpha = 0.92$), and one for county disadvantage ($\alpha = 0.90$). Refer to Tables 2 and 3 for more information on the creation of the two scales. These standardized scales consisted of the total unemployment rate, percent living below the poverty level, percent of female headed households, and percent of families receiving public assistance. Both scales included negative numbers since the scales were standardized. Therefore, it was necessary to un-center both scales from zero by adding five points to all scores in both scales. Relative neighborhood disadvantage scale by the transformed county disadvantage scale. All relative neighborhood disadvantage than the surrounding area within the county. The

Table 2. Creation of Neighborhood Disadvantage Scale

8		0		
	Sign	Correlation	Alpha	
Total Unemployment Rate	+	0.88		
Below Poverty Level	+	0.93		
Female Headed Household	+	0.88		
With Public Assistance	+	0.88		
			0.92	

Table 3. Creation of County Disadvantage Scale

	Sign	Correlation	Alpha	
Total Unemployment Rate	+	0.87		
Below Poverty Level	+	0.91		
Female Headed Household	+	0.93		
With Public Assistance	+	0.80		
			0.90	

relative neighborhood disadvantage scale was mean-centered for each of the seven models to reduce collinearity within each model. *Relative* neighborhood disadvantage was used instead of neighborhood disadvantage since the ADAM survey consisted of data from 39 different cities. Using relative neighborhood disadvantage allows for standardization of the disadvantage scores across the different cities.

Agnew (2006) argues that neighborhood disadvantage is a major source of strain. Neighborhood disadvantage is often viewed as unjust since individuals are often forced to move to deprived communities due to a lack of resources and are later unable to move out of these communities for the same reason (Agnew, 1999). Many deprived neighborhoods have a higher concentration of minorities and researchers argue that the residents in the communities are subsequently subjected to discrimination by residents in surrounding communities (Cook and Curtin, 1987).

According to Agnew, neighborhood disadvantage is also viewed as high in magnitude since many of the individuals who live in these disadvantaged communities suffer from numerous hardships including financial problems, increased chances of victimization, and relative deprivation (Agnew, 1999). Relative depravation occurs when residents in these deprived neighborhoods compare themselves to privileged others that live nearby. When those in poorer neighborhoods are unable to achieve their desired goals, they often resort to deviant means (Agnew, 1999). This illegal behavior then increases contact with other criminal associates and increases their chances of victimization (Agnew, 1999).

Living in a disadvantaged community decreases social control and creates the pressure necessary for criminal coping by increasing the values conducive to criminal behavior (Agnew, 1999; Anderson, 1999). Those in deprived neighborhoods have less social support, often because older, more stable residents (who may have acted as community leaders or role models) have moved to other neighborhoods (Wilson, 1996). Without positive role models, many youth in these disadvantaged neighborhoods are taught to embrace a street code that values hyper-masculinity and criminal behavior (Agnew, 1999; Anderson, 1999).

According to Agnew (2001), homelessness is another major source of strain. Only respondents who reported no permanent residence within the past 30 days were coded as homeless. Respondents who reported living in a shelter for the past 30 days were not coded as homeless since they were not expected to experience such high levels of strain compared to those that reported having no place to stay (Dalton and Pakenham, 1999).

Strain from being homeless is likely to be viewed as high in magnitude due to the multiple obstacles that the homeless face on a daily basis. The homeless often struggle to

meet their basic needs such as food, shelter, and minimal healthcare (McCarthy and Hagan, 1992). Being homeless may also lead to perceived unjust situations. The homeless are vulnerable to a number of traumatic events and victimization that may cause or exacerbate mental health issues, substance abuse problems, and may increase criminal coping methods (Dalton and Pakenham, 2002; Kim and Ford, 2006).

Homelessness is also associated with low social control and the social learning of crime (Agnew, 2001). According to Hagan and McCarthy (1997), many who are homeless turn to illegal behavior when noncriminal means are unavailable to meet the demands of living on the street. This illegal behavior is often learned through interaction with others on the streets who regularly engage in criminal acts (Hagan and McCarthy, 1997). These associates not only provide an introduction to criminal behavior, but also diminish the social cost of such behavior by reinforcing criminogenic attitudes and limiting personal contact with pro-social others who may be able to provide positive resources (Hagan and McCarthy, 1997).

Racial prejudice is still commonplace in many areas in the U.S. (Kaufman et al., 2008; Massey and Denton, 1993; Wilson, 1987). The current study was unable to examine racial discrimination; however, according to Kaufman and colleagues (2008), blacks tend to experience racially unique strains and overall higher levels of strain compared to whites. In the current study, race was coded as a nominal variable that included the following categories: white, black, Hispanic, or other minority status. White is the reference category for this variable.

Being a minority may not directly increase strain; however, it introduces an array of stressful situations (Kauffman et al., 2008). Minorities are not only subject to racial or

ethnic discrimination by the general public and the criminal justice system, but they also often experience increased levels of economic, family, and educational strain compared to their white counterparts (Kauffman et al., 2008). Therefore, being a minority subjects the individual to strain that is often viewed as high in magnitude because strain is present in the individual's everyday life. Racial discrimination may also be viewed as an unjust strain. Foreman and colleagues (1997) found that blacks are approximately two times more likely to experience racial discrimination at some time in their lives compared to whites. Prior literature has also indicated that racial discrimination is still present in the housing market and in employer hiring decisions (Foreman et al., 1997; Pager, 2003). As a result, racial discrimination often reduces attachment to pro-social institutions like education and employment (Agnew, 2001). Thus, minorities often have limited coping resources and may adopt values conducive to criminal coping (Koffman et al., 2008).

Educational strain is often conceptualized as negative relationships with teachers (Moon et al., 2009; Moon et al., 2008), a dislike for school (Agnew et al., 2002), or a lower student grade point average (Ford and Schroaeder, 2009). However, prior literature has indicated that failure to obtain a high school diploma or GED often leads to stress or stigma later in life (Kaplan, 1983; Kaplan and Damphousse, 1994; Kaplan et al., 1996). Therefore, this study uses educational underachievement as an indicator of strain. Educational underachievement is coded as an ordinal variable including the following three categories: attended or graduated college, high school diploma or GED, or did not obtain high school diploma or GED.

Educational underachievement should be viewed as high in magnitude because of the negative consequences associated with the decision to leave school at a young age,

which may lead to psychological dysfunction later in life. Kaplan and Damphousse (1994) define psychological dysfunction as the lack of self-esteem, the inducement of anxiety or depression, cognitive disorientation, sensitivity to criticism, recognition of difficulties in handling stress, and the instability of self-feelings. The study found that students who dropped out of high school may have obtained short-term psychological relief from leaving school but experienced increased psychological dysfunction later in life (Kaplan and Damphousse, 1994). These results were supported in another study by Kaplan and colleagues (1996) who found that dropping out of high school led to increased levels of self-derogation, anxiety, cognitive disorientation, and depression. However, dropping out of high school is not always a personal choice. Some students may leave school due to restrictive school policies, for personal or familial reasons, or for economic reasons (Sweeten et al., 2009). The stress and stigma that result from dropping out of high school may be viewed as unjust if the student left school to support his or her family or if the student was permanently expelled from school for a seemingly unjust reason.

Prior literature also indicates that dropping out of high school disrupts the individual's acquisition of pro-social coping mechanisms (Kaplan, 1983) and leads to higher rates of unemployment and lower income across the life course (Murnane et al., 2000; Rumberger, 1987). Therefore, strain from educational underachievement reduces social control and creates the pressure necessary for criminal coping if the individual is unable to provide for themselves or their families.

According to Agnew (2006), long-term unemployment is a severe strain that is likely to be seen as unjust and high in magnitude. Long-term unemployment is also

likely to be associated with low social control and often creates the pressure necessary for criminal coping. In the current study, a respondent was considered "employed" if he or she was employed full-time, part-time, on active military status, or had a job but was currently not working due to illness, leave, furlough, or strike. A respondent was coded as "unemployed" if he or she reported currently being out of work (in the case of seasonal employment), unemployed for any reason, or a full-time homemaker. A respondent was coded as "other type of employment" if they were in school, retired, or disabled.

According to McCubbin and Colleagues (1980) stress does not directly result from unemployment but the problems that result from being unemployed. The loss of income is one of the largest hardships of being unemployed (Wilhelm and Ridley, 1988). Therefore, the unemployed must find new ways to generate income to meet their financial obligations or risk losing their personal possessions. These perceived economic difficulties may also generate stress among the unemployed (Baron, 2008). According to Baron and Hartnagel (1997), long-term unemployment reduces commitment to pro-social institutions and severs ties to these institutions. Therefore, strain from being unemployed may be viewed as high in magnitude since unemployment affects the individual's current situation and their perceptions of their future problems. Unemployment also creates the necessary pressure for criminal coping if current financial obligations cannot be met through legal means.

Other variables believed to increase strain are the offense severity (e.g., felony, misdemeanor, municipal, or traffic), type of offense (e.g., violent, property, drug, other), and if the respondent has ever previously been arrested or been to jail. The ADAM data include offense information on each individual for up to three different offenses. The

offense severity variable is coded as the most severe of the three recorded offenses and is coded as a nominal variable with "felony" as the reference category. The type of offense is coded in a similar manner as the offense severity, where "violent offense" is the reference category. Previously being arrested and previously having been to jail are each coded as dichotomous variables.

Those facing charges with a more severe sentencing outcome (e.g., a violent felony) should experience more stress than those arrested for an offense that will likely lead to little, if any, punishment (e.g., minor traffic offenses). Those who have been previously arrested or have previously spent time in jail should be under less stress due to being desensitized to their current situation and because these individuals have most likely developed the necessary coping mechanisms to manage their time behind bars (Hayes, 1995).

Control Variables

Control variables in the current study include: age of respondent, marital status, being previously enrolled in an out-patient substance abuse treatment program, hours since the respondent was arrested, interviewer characteristics, and the quarter in which the individual was interviewed.

The age of the respondent is coded as a continuous variable. Respondents under the age of 18 and over the age of 99 were eliminated due to presumed data entry errors since the 2003 ADAM data did not include juvenile data. Age was then mean-centered for each of the seven models to reduce collinearity within the different models.

Marital status was coded as "single", "married", or "separated, divorced, or widowed," with "married" being the reference category. According to Agnew (2006), marital problems are a major source of strain. However, because the 2003 ADAM data did not permit subjective interpretations of the respondent's marital status, marital status is used as a control variable since it is unknown whether the respondent was experiencing marital strain at the time of the interview.

Enrollment in an outpatient substance abuse treatment program was coded as a dichotomous variable and included as a control variable because prior literature indicated that being in a substance abuse treatment program is associated with subsequent accurate self-reported drug use (Magura and Kang, 1996). Length of time since the respondent was arrested is coded as a continuous variable. However, the variable was positively skewed with some respondents reporting that they had been in jail for several months. Therefore, the natural log of the variable was calculated. In addition, the variable was mean-centered for each of the seven models to reduce collinearity within the different models.

Interviewer characteristics for age, gender, and race were controlled. Interviewer characteristics for age were coded as either "older", "younger", or the "same age as the respondent," where "same age as the respondent" is the reference category. Interviewer characteristics for gender were coded as either male or female. Interviewer characteristics for race were coded as "same race as respondent" or "different race as respondent." Controlling for interviewer characteristics ensures that accurately self-reported drug use did not vary based on interviewers' characteristics (Fendrich et al., 1999).

The yearly quarter in which the respondent was interviewed was used as a control variable to reduce error in the statistical models. The ADAM data in the current study were collected over a two-week period, four times a year, in 2003. The first quarter is used as the reference category.

Methods

The current study used bivariate and multivariate analyses to determine if strain led to inaccurate self-reporting of drug use. A one-way ANOVA was calculated to determine if there were significant differences in the composition of the samples between the seven different models. If no differences existed between the seven models, then differences in the predictors of inaccurate self-reports would be the result of the differences in the drug type, not differences between the samples.

Bivariate correlations were calculated to determine the strength and direction between the predictors of strain and inaccurate self-reported drug use. However, it may be possible that significant correlations between the different types of strain and inaccurate self-reports are spurious. Therefore, seven binary conditional logistic regression models with fixed effects and robust standard errors were calculated to determine if increased levels of strain led to less accurate self-reported drug use. Binary conditional logistic regression models were used because the dependent variable was dichotomous (i.e., accurate or inaccurate). Conditional logistic regression models were used because logistic regression models do not permit the use of robust standard errors.

Robust standard errors are more conservative and protect against heteroskedasticity. Fixed effects were used to control for variation between the 39 different cities.

According to Agnew (2001) and Thoits (1983), experiencing multiple stressful situations at one time is likely to subject the respondent to more distress and diminish the individual's pro-social coping mechanisms. To test this proposition, interaction effects were introduced into all seven regression models. If significant interactions were present within the models, then cumulative strain is a predictor of inaccurate self-reported drug use.

Chapter Four

Results

This chapter describes the data analyses and findings in the current study. This chapter presents the characteristics of the seven different drug models and results of a one-way ANOVA to illustrate the differences and similarities of the independent variables between the seven different models. Next, correlations are calculated to determine the strength, direction, and significance of the relationships between strain variables and the accuracy of self-reported drug use in each model. Third, multivariate analyses are conducted in order to control for other factors that might contribute to the effect of the strain variables on the accuracy of self-reported drug use in each of the seven models. Finally, interaction effects are examined in each of the seven models to determine if accumulated strain affects the accuracy of self-reported drug use.

Descriptive Statistics

Descriptive statistics for the each of the seven models can be found in Table 4. Alcohol was the most accurately reported drug. Approximately 85% of the sample that tested positive for alcohol admitted use of alcohol. Marijuana was the second most accurately reported drug. Approximately 81% of the sample that tested positive for marijuana admitted use of marijuana. Approximately 68% of the sample that tested positive for opiates, approximately 66% of the sample that tested positive for methadone, and approximately 58% of the sample that tested positive for methadone

	Cocaine (n	=4935)	Opiates (n=1272)		Methamphetamines (n=2332) Mariju		332) Marijuan	Marijuana (n=7485)		Benzodiazepines (n=726)) Methadone (n=229) Alcohol (n=1085)		
	Μ	SD	M	SD	М	SD	M	SD	М	SD	М	SD	M	SD
Age	34.26	10.09	34.36	10.50	31.02	08.75	27.74	08.84	32.77	10.88	36.96	10.32	36.22	10.70
Relative Neighborhood Disadvantage ¹	1.03	0.18	1.00	0.18	1.01	0.13	1.02	0.18	0.98	0.17	0.98	0.19	01.03	0.19
Hours Since Arrest (Natural Log)	1.96	1.01	1.89	1.02	1.97	0.96	1.93	1.02	2.01	1.02	2.02	0.93	01.43	0.97
	Percentage		Percenta	ge	Percentage		Percentag	ge	Percentag	ge	Percenta	nge	Percentage	
Accurate Self-Reports	44.64		67.90	-	58.07		81.93	-	47.12	-	65.50	•	84.91	
Homeless	06.53		05.73		07.49		04.42		06.59		05.24		08.00	
Minority Status														
White	27.63		40.58		65.43		36.60		58.24		39.74		48.67	
Black	54.24		39.32		06.76		45.88		23.21		29.26		27.14	
Hispanic	14.98		14.91		21.05		12.83		13.32		21.40		16.28	
Other	03.15		05.18		06.76		04.69		05.23		09.61		07.91	
Educational Underachievement	01.04		01.05		01.02		01.10		00.95		01.01		00.91	
Unemployed														
Employed	52.97		48.04		55.20		55.50		54.26		53.71		61.36	
Unemployed	37.61		40.27		38.38		37.14		32.28		34.06		29.44	
Other	09.42		11.70		06.42		07.37		13.46		12.23		09.20	
Offense Severity														
Felony	47.78		50.31		56.48		45.62		41.76		49.34		25.12	
Misdemeanor	43.49		41.13		41.76		47.59		53.16		47.16		66.79	
Traffic/Ordinance	08.73		08.56		01.75		06.78		05.08		03.49		08.10	
Offense Charge														
Violent	11.74		09.50		11.77		14.76		14.01		10.04		17.48	
Drug	23.12		27.79		22.51		22.53		22.39		31.88		19.32	
Property	19.26		20.09		19.00		15.71		18.96		22.71		12.33	
Other	45.88		42.62		46.73		47.00		44.64		35.37		50.87	
Never Been Arrested Before	10.25		10.13		09.71		15.39		14.84		07.86		12.33	
Never Been to Jail Before	14.27		14.68		13.74		19.85		19.37		12.23		22.08	
Marital Status	1.1.27		1 1100		10171		19100		19107		12.20		22.00	
Single	59.54		59.50		57.08		71.86		58.93		56.77		55.29	
Married	20.33		21.35		20.67		16.84		20.88		22.27		20.88	
Div/Sep/Wid	20.13		19.15		22.25		11.30		20.19		20.96		23.83	
Previous Outpatient Treatment	25.10		33.44		25.67		19.07		29.40		52.84		25.02	
Interviewer Characteristics	20.10		55				12.007		27.10				_0.02	
Same Age	23.79		25.04		26.06		30.62		25.96		23.14		22.91	
Older	25.20		29.59		26.62		38.81		27.75		26.64		18.77	
Younger	51.01		45.37		47.33		30.57		46.29		50.22		58.33	
Female	77.59		77.32		79.20		78.35		79.12		73.36		77.09	
Quarter	11.02		11.52		. 7.20		10.00				15.50			
First	28.50		27.79		32.14		29.65		27.88		22.27		32.66	
Second	29.73		31.08		27.39		28.82		29.26		29.69		27.78	
Third	29.61		30.46		32.26		30.15		28.02		34.50		27.69	
Fourth	12.17		10.68		08.22		11.38		14.84		13.54		11.87	
FOULUI	12.17		10.08		00.22		11.30		14.04		15.54		11.0/	

Table 4. Descriptive Statistics for Accuracy of Self-Reports, Indicators of Strain, and Personal Attributes

Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage

accurately reported their drug use. Accuracy rates for benzodiazepines and cocaine were the two least accurately reported drugs. Approximately 47% of the sample that tested positive for benzodiazepines and approximately 45% of the sample that tested positive for cocaine accurately reported their drug use. The high accuracy rates for alcohol and marijuana and the low accuracy rates for cocaine illustrate what prior literature has shown in that respondents are more likely to admit to use of substances they view as less stigmatized (i.e., alcohol and marijuana).

A one-way ANOVA was calculated to determine if the independent or control variables significantly differed across the seven models. Results from the one-way ANOVA indicated that many of the variables were statistically different between drug models. This indicates that the models are based on seven relatively distinct subpopulations. Therefore, comparisons among the seven different models should be made with these baseline differences in mind.

All relative neighborhood disadvantage scores above "1" signify that the respondents resided in a neighborhood more disadvantaged than the surrounding areas in the county in which they resided. Therefore, all disadvantage scores below "1" indicate that the respondents resided in a neighborhood less disadvantaged than the surrounding areas in the county in which they lived. Relative disadvantage scores ranged from 0.98 in the methadone and benzodiazepine model to 1.03 in the cocaine and alcohol model.

The alcohol model includes the highest percentage of respondents who reported being homeless for the past 30 days (8%). Only 4% of respondents in the marijuana model reported being homeless for the past 30 days and 5% of respondents in the opiate and methadone models reported being homeless in the past 30 days. Finally,

approximately 7% of respondents in the cocaine model, benzodiazepine model, and the methamphetamine model reported that they were homeless for the past 30 days.

The majority of respondents were either white or black depending on the drug model. The population of whites in the seven different models ranged from approximately 28% in the cocaine model to approximately 65% in the methamphetamine model. The percentage of blacks ranged from approximately 7% in the methamphetamine model to approximately 54% in the cocaine model. The percentage of Hispanics ranged from 13% in the marijuana and benzodiazepine models to 21% in the methamphetamine and methadone models. The percentage of other minorities ranged from approximately 3% in the cocaine model to approximately 10% in the methadone model.

All educational underachievement scores above "1" signify a higher percentage of respondents lacking a high school diploma or GED. Therefore, all educational underachievement scores below "1" signify a higher percentage of respondents obtaining secondary education. Respondents in the marijuana model had the highest levels of educational underachievement (M=1.10), while those in the alcohol model reported the lowest levels of educational underachievement (M=0.91).

A majority, or near majority, of the respondents in the seven drug models were employed. Percent of respondents employed ranged from approximately 48% in the opiate model to approximately 61% in the alcohol model. The percentage of respondents unemployed ranged from approximately 29% in the alcohol model to approximately 40% in the opiate model.

Most respondents were arrested for a felony or misdemeanor offense as opposed to traffic or local ordinance infractions. Respondents in the methamphetamine model were the most likely to have been arrested for a felony offense (56%), whereas respondents in the alcohol model were the least likely to have been arrested for a felony offense (25%). The percent of respondents arrested for a misdemeanor offense ranged from approximately 41% in the opiate model to approximately 67% in the alcohol model. The percentage of respondents arrested for a traffic offense or a local ordinance offense ranged from approximately 2% in the methamphetamine model to approximately 9% in the cocaine and opiate models.

Few respondents in each model were arrested for a violent offense. The percent of respondents arrested for a violent offense ranged from approximately 10% in the opiate model to approximately 17% in the alcohol model. The percent of respondents arrested for a drug offense ranged from approximately 19% in the alcohol model to approximately 32% in the methadone model. The percent of respondents arrested for a property offense ranged from approximately 12% in the alcohol model to approximately 23% in the methadone model. Finally, the percent of respondents arrested for "other offenses" (e.g., prostitution, gambling, probation violation, etc.) ranged from approximately 35% in the methadone model to approximately 51% in the alcohol model.

Across all seven models, few respondents reported that they had never been previously arrested or held in jail. The percentage of respondents that reported no prior arrests ranged from approximately 8% in the methadone model to approximately 15% in the benzodiazepine and marijuana models. The percentage of respondents who reported

they had never been to jail before ranged from approximately 12% in the methadone model to approximately 22% in the alcohol model.

Respondents in the marijuana model were the youngest compared to those included in the other models. The average age of respondents in the marijuana model was 28 years old (s = 8.84). Respondents in the methadone model were older in age than those in the other six models with an average age of approximately 37 years old (s = 10.32).

In six of the seven models, approximately 55% to 60% of the respondents reported that they were currently single, approximately 20% to 22% reported they were married, and approximately 19% to 24% reported they were divorced, separated, or widowed. In the marijuana model, 72% of the respondents reported they were single, 17% reported that they were married, and 11% reported that they were divorced, separated, or widowed.

Respondents who reported previously being in an outpatient substance abuse treatment program ranged from approximately 19% in the marijuana model to approximately 53% in the methadone model. Therefore, over twice as many respondents in the methadone model than the marijuana model had previously been enrolled in an outpatient substance abuse treatment program.

Bivariate Results

Correlations for each of the seven models were calculated to determine if accurately reported drug use was correlated with the strain indicators. Pearson

correlations were calculated for all continuous level variables (relative neighborhood disadvantage and age), whereas Spearman correlations were calculated for the remaining variables. Refer to Table 5 for correlations. For each of the seven drug models, it was predicted that the different indicators of strain would be negatively correlated with accurate self-reported drug use. When comparing correlations for each drug model, caution should be used since the size of the samples differ and previous analyses indicated that many of the variables were statistically different across the seven drug models.

Cocaine Model

For the cocaine model (n = 4,935), minority strain, educational underachievement, strain from the seriousness of the arrest charge, and strain from being arrested for the first time or being in jail for the first time were significant in the predicted directions. Specifically, Hispanics and those with higher levels of educational underachievement were significantly less likely to accurately report cocaine use. In addition, respondents who were arrested for a violent offense, had never before been arrested, and respondents who had never been to jail before were significantly less likely to accurately report cocaine use. Several strain indicators were also positively correlated with accurate self-reported cocaine use. Those who were homeless and those who were unemployed were significantly more likely to accurately report cocaine use. Those arrested for a felony offense were also significantly more likely to accurately report cocaine use.

	Cocaine	Opiates	Methamphetamines	Marijuana	Benzodiazepines	Methadone	Alcohol
	(n = 4935)	(n = 1272	2) $(n = 2332)$	(n = 7485)	(n = 726)	(n = 229)	(n = 1085)
Relative Nghd. Disadvantage ¹	0.00	-0.02	-0.01	-0.01	-0.04	-0.05	-0.01
Homeless	0.13*	0.04	0.09*	0.02	-0.08*	0.01	0.08*
Minority Status:							
White	0.05*	0.10*	0.14*	0.04*	0.17*	0.08	0.11*
Black	-0.00	-0.09*	-0.11*	-0.02	-0.17*	-0.26*	-0.06*
Hispanic	-0.04*	0.03	-0.08*	-0.03*	-0.02	0.13*	-0.09*
Other Minority	-0.02	-0.07*	-0.02	-0.01	-0.02	0.08	0.02
Educational Underachievement	-0.07*	-0.02	-0.04*	0.00	-0.05	-0.00	0.02
Employment Status:							
Employed	-0.09*	-0.04	-0.11*	-0.03*	-0.06	-0.05	-0.06*
Unemployed	0.11*	0.02	0.13*	0.04*	0.00	-0.04	0.04
Other Employment	-0.03*	0.04	-0.02	-0.03*	0.08*	0.13*	0.05
Offense Severity:							
Felony	0.05*	0.13*	0.14*	0.03*	0.06	-0.02	-0.03
Misdemeanor	-0.04*	-0.08*	-0.12*	-0.02	-0.03	0.04	0.05
Traffic/Local Ord.	-0.01	-0.09*	-0.06*	-0.02	-0.08*	-0.06	-0.03
Offense Charge:							
Violent Offense	-0.05*	-0.04	-0.11*	-0.03*	-0.05	-0.09	-0.05
Drug Offense	0.01	0.05	0.07*	0.05*	0.04	-0.02	-0.04
Property Offense	0.07*	0.06*	0.04	0.01	-0.01	0.04	0.04
Other Offense	-0.03	-0.07*	-0.02	-0.02*	0.01	0.04	0.04
Never Been Arrested Before	-0.06*	-0.14*	-0.10*	-0.06*	-0.05	-0.10	-0.03
Never Been to Jail Before	-0.08	-0.14*	-0.12*	-0.07*	-0.01	0.02	-0.08*
Age	0.17*	0.08*	0.08*	-0.08*	-0.06	0.07	0.01
Marital Status:							
Single	-0.09*	-0.02	-0.01	0.05*	-0.03	-0.00	0.00
Married	0.01	0.03	-0.02	-0.05*	0.10*	-0.05	-0.02
Div./Sep./Wid.	0.09*	-0.00	0.04	-0.02	-0.07	0.06	0.01
Previous Outpatient Treatment	0.15*	0.04	0.11*	0.05*	0.08*	0.20*	-0.11*

Table 5. Correlations Between the Accuracy of Self-Reported Drug Use and Indicators of Strain and Personal Attributes

¹ Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage * p<0.05

Several other factors were correlated with the accuracy of self-reported cocaine use. Respondents who were white, older, or who had previously enrolled in an outpatient substance abuse program were significantly more likely to accurately report cocaine use. Those who were employed or were arrested for a misdemeanor offense were significantly less likely to accurately report cocaine use.

Opiate Model

For the opiate model (n = 1,272), few strain indicators had a significant negative correlation with accurate self-reported opiate use. Minority strain and strain from being arrested for the first time or being in jail for the first time were significant in the predicted direction. Both blacks and Hispanics were significantly less likely to accurately report opiate use. Those who had never been to jail or arrested were significantly less likely to accurately to accurately report opiate use.

The only strain indicator that had a significant positive correlation with accurate self-reported opiate use was severity of the offense. Respondents arrested for a felony offense were significantly more likely to accurately report opiate use. Many personal characteristics were also correlated with the accuracy of self-reported opiate use. Respondents who were white, older, or who were most recently arrested for a property offense were more likely to accurately report opiate use. Respondents who were arrested for a misdemeanor offense, traffic offense, or were arrested for an "other" offense type were significantly less likely to accurately report opiate use.

Methamphetamine Model

For the methamphetamine model (n = 2,332), minority strain, educational underachievement, strain from the seriousness of the arrest charge, and strain from being arrested or in jail for the first time were significantly correlated with the accuracy of selfreported methamphetamine use in the predicted directions. Respondents who were black or Hispanic or had higher levels of educational underachievement were significantly less likely to accurately report methamphetamine use. In addition, respondents arrested for a violent offense and those who had never been arrested or in jail before were significantly less likely to accurately report methamphetamine use. Several strain predictors were also significant in the opposite direction predicted. The homeless, unemployed, and those arrested for a felony offense were significantly more likely to accurately report methamphetamine use.

Many other factors were also associated with the accuracy of self-reported methamphetamine use. Respondents who were white, older, previously arrested for a drug offense, or were previously enrolled in an outpatient substance abuse treatment program were significantly more likely to accurately report methamphetamine use. In addition, those who were employed or those who were arrested for a misdemeanor or traffic offense were significantly less likely to accurately report methamphetamine use.

Marijuana Model

For the marijuana model (n = 7,485), findings reveal that minority strain, strain from the seriousness of the arrest charge, and strain from being arrested or in jail for the first time were significantly correlated with the accuracy of self-reported marijuana use as

predicted. Hispanic respondents, those arrested for a violent offense, or those who had never before been arrested or in jail were significantly less likely to accurately report marijuana use.

Respondents who were unemployed and respondents who were arrested for a felony offense were significantly more likely to accurately report marijuana use, which is opposite than predicted. Many other important indicators were significantly associated with the accuracy of self-reported marijuana use. White respondents, those arrested for a drug offense, and those who had previously been in an outpatient substance abuse treatment program were significantly more likely to accurately report marijuana use. Respondents who were employed, older, or who were arrested for an "other" offense were significantly less likely to accurately report marijuana use.

Benzodiazepine Model

For the benzodiazepine model (n = 726), being of minority status and strain from being homeless were significantly correlated with the accuracy of self-reported benzodiazepine use in the predicted direction. Respondents who were homeless and who were black were significantly less likely to accurately report benzodiazepine use.

Several other factors were also associated with the accuracy of self-reported benzodiazepine use. Respondents who were arrested for a traffic offense were significantly less likely to accurately report benzodiazepine use. In addition, white respondents, those who were either a student, retired, or disabled, or those who were previously enrolled in an outpatient substance abuse treatment program were significantly more likely to accurately report benzodiazepine use.

Methadone Model

For the methadone model (n = 229), conflicting results occurred with minority strain. Black respondents were significantly less likely to accurately report methadone use, whereas Hispanic respondents were significantly more likely to accurately report methadone use. Two other factors were also associated with the accuracy of self-reported methadone use. Respondents who were either students, retired, or disabled, or were previously enrolled in an outpatient substance abuse treatment program were significantly more likely to accurately report methadone use.

Alcohol Model

In the alcohol model (n = 1,085), being of minority status and the strain from being in jail for the first time were significantly correlated with the accuracy of selfreported alcohol use in the predicted direction. Respondents who were black or Hispanic were significantly less likely to accurately report alcohol use. In addition, respondents who had never been to jail before were significantly less likely to accurately report alcohol use.

Only one strain indicator was significant in the opposite direction predicted. Respondents who were homeless were significantly more likely to accurately report alcohol use. The only other factor associated with the accuracy of self-reported alcohol use was previous drug treatment status. Respondents who were previously enrolled in an outpatient substance abuse treatment program were significantly more likely to accurately report alcohol use.

Multivariate Results

Binary conditional logistic regression models with fixed effects and robust standard errors were estimated for each of the seven models to determine if strain led to inaccurate self-reported drug use when all other covariates were controlled. After each model was estimated, interaction effects were introduced into the model to determine if accumulated strain leads to inaccurate self-reported drug use. Since each indicator of strain did not have a fixed effect on the accuracy of self-reported drug use, an interactive model instead of an additive model was generated (Agnew, 1992). The interactive model assumes that each type of strain has varying effects on the accuracy of self-reported drug use. Interaction terms were created between each of the five main strain indicators: relative neighborhood disadvantage, homelessness, minority status, educational underachievement, and unemployment. Only the significant interactions (p<0.05) were included in the models. No interactions were generated between the strain indicators and the control variables since there is no evidence in prior literature that indicates possible interaction effects.

Cocaine Model

Several indicators of strain in the cocaine model (n=4,935) significantly decrease the odds of accurately reporting cocaine use.⁴ In cocaine Model 1, minority status, educational underachievement, and offense charge all significantly affect the accuracy of self-reported cocaine use in the predicted direction. For blacks, the odds of accurately reporting cocaine use decreases by a factor of 0.77 (b = -0.27) compared to whites, when

⁴ Refer to Table 6 for the cocaine regression models.

	Model 1	(n = 4935))	Model 2	(n = 493	5)	Model 3	(n = 493	5)
	b	OR	(R.S.E.)	b	OR	(R.S.E)	b	OR	(R.S.E.)
Relative Neighborhood Disadvantage ¹	0.11	1.11	(0.19)	0.10	1.11	(0.19)	0.11	1.12	(0.20)
Iomeless	0.82***	2.28	(0.31)	0.82***	2.27	(0.31)	1.21***	3.36	(0.88)
Minority Status (White):									
Black	-0.27**	0.77	(0.07)	-0.27**	0.77	(0.07)	-0.27**	0.76	(0.07)
Hispanic	-0.15	0.86	(0.11)	-0.17	0.85	(0.11)	-0.16	0.85	(0.11)
Other Minority	-0.24	0.79	(0.16)	-0.24	0.79	(0.16)	-0.25	0.78	(0.16)
Educational Underachievement	-0.09*	0.91	(0.04)	-0.01	0.99	(0.06)	-0.07	0.93	(0.04)
Employment Status (Employed):									
Unemployed	0.44***	1.55	(0.11)	0.62***	1.85	(0.24)	0.43***	1.54	(0.11)
Other Employment	-0.37**	0.69	(0.09)	-0.22	0.80	(0.16)	-0.37**	0.69	(0.09)
Offense Severity (Felony)									
Misdemeanor	-0.15*	0.86	(0.06)	-0.16*	0.85	(0.06)	-0.16*	0.85	(0.06)
Traffic/Local Ordinance	-0.08	0.92	(0.11)	-0.09	0.92	(0.11)	-0.08	0.92	(0.11)
Offense Charge (Violent)			· · ·						
Drug	0.26*	1.30	(0.15)	0.27*	1.30	(0.15)	0.26*	1.30	(0.15)
Property	0.40***	1.49	(0.16)	0.39***	1.48	(0.16)	0.39***	1.48	(0.16)
Other	0.17	1.18	(0.11)	0.17	1.18	(0.11)	0.16	1.18	(0.11)
lever Been Arrested Before	-0.10	0.90	(0.13)	-0.10	0.90	(0.13)	-0.10	0.90	(0.13)
lever Been to Jail Before	-0.22	0.80	(0.09)	-0.21	0.81	(0.10)	-0.22	0.80	(0.09)
ge	0.03***	1.03	(0.01)	0.03***	1.02	(0.01)	0.03***	1.03	(0.01)
Aarital Status (Married)	0.05	1.05	(0.01)	0.05	1.02	(0.01)	0.05	1.05	(0.01)
Single	-0.13	0.88	(0.08)	-0.13	0.88	(0.08)	-0.13	0.88	(0.08)
Div/Sep/Wid	-0.13	1.03	(0.08) (0.11)	0.03	1.03	(0.08)	0.03	1.03	(0.08)
lours Since Arrest	0.02	1.03	(0.04)	0.03	1.03	(0.04)	0.03	1.03	(0.11)
revious Outpatient Treatment	0.56***	1.08	(0.04)	0.57***	1.08	(0.04)	0.56***	1.76	(0.04)
nterviewer Age (Same Age As Respondent)	0.56***	1.70	(0.11)	0.57	1.70	(0.11)	0.30***	1.70	(0.11)
	-0.38***	0.69	(0.07)	-0.38***	0.00	(0.07)	-0.38***	0.69	(0.07)
Older Than Respondent		0.69	(0.07)		0.69				
Younger Than Respondent	-0.08		(0.10)	-0.08	0.93	(0.10)	-0.08	0.92	(0.10)
emale Interviewer	-0.17	0.85	(0.09)	-0.17	0.85	(0.09)	-0.16	0.85	(0.09)
Different Race Than Interviewer	0.05	1.06	(0.08)	0.05	1.05	(0.08)	0.06	1.06	(0.08)
Quarter (First Quarter)		-	(0.0.7)		-			~ ~ -	(0.0.7)
Second	-0.03	0.97	(0.06)	-0.03	0.97	(0.06)	-0.03	0.97	(0.06)
Third	0.13	1.14	(0.08)	0.13*	1.14	(0.08)	0.13	1.14	(0.08)
Fourth	-0.02	0.98	(0.15)	-0.03	0.97	(0.15)	-0.03	0.97	(0.16)
nteractions:									
ducational Underachievement X Unemployed				-0.17*	0.84	(0.07)			
ducational Underachievement X Other Employment				-0.15	0.86	(0.14)			
Iomeless X Educational Underachievement							-0.35*	0.70	(0.12)
og Pseudolikelihood	-3032.483	3		-3030.3424	4		-3030.315	9	
seudo R ²	0.07			0.07			0.07		
SIC'	-341.711			-338.666			-342.382		
<i>n</i> c	-5-1./11			-556.000			-5-2.562		

Table 6. Regression Estimates for the Accuracy of Self-Reported Cocaine Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

all other variables were held constant. For a one unit increase in educational underachievement, the odds of accurately reporting cocaine use decreases by a factor of 0.91 (b = -0.09), holding all other variables constant. The odds of accurately reporting cocaine use were 30% (b = 0.26) greater for those arrested for a drug offense than for those arrested for a violent offense, holding all other variables constant. Finally, the odds of accurately reporting cocaine use is approximately 49% (b = 0.40) greater for those arrested for a property offense than those arrested for a violent offense, holding all other variables constant.

Three strain indicators in cocaine Model 1 significantly increased the odds of accurately reporting cocaine use. For those that were homeless, the odds of accurately reporting cocaine use increased by a factor of 2.28 (b = 0.82) compared to those who were not homeless, holding all other variables constant. The odds of accurately reporting cocaine use for unemployed respondents are approximately 55% (b = 0.44) greater compared to respondents who were employed, holding all other variables constant. Finally, those arrested for a misdemeanor offense have 0.86 (b = -0.15) less odds of accurately reporting cocaine use than those arrested for a felony, holding all other variables constant. Other important variables that significantly increase the odds of accurately reporting cocaine use include being older (b = 0.03) and being enrolled in an outpatient substance abuse treatment program (b = 0.56).

Interaction terms were introduced into the model to test if accumulated strain decreases the odds of accurately reporting cocaine use. Only two of the interaction terms are significant. These interaction terms are included in Model 2 and Model 3 in Table 6. Model 2 shows the results of an interaction effect between educational underachievement

and employment status and Model 3 shows the results of an interaction between homelessness and educational underachievement.⁵

In cocaine Model 2, there is a significant interaction between educational underachievement and unemployment; however, no significant interaction exists between "other types of employment" and educational underachievement. For those who were unemployed, a one unit increase in educational underachievement decreases the odds of accurately reporting cocaine use by a factor of 0.84 or 16% (b = -0.17) compared to those who were employed, when holding all other variables constant. For those with a college education who were unemployed, the odds of accurately reporting cocaine use increases by a factor of 1.85 or 85% (b = 0.62) when compared to those with a college education who were employed. However, for those who were employed, educational underachievement did not significantly affect the accuracy of self-reported cocaine use.

Model 3 shows the interaction between homelessness and educational underachievement. When educational underachievement increases by one unit, the odds of accurately reporting cocaine use for the homeless decreases by a factor of 0.70 or 30% (b = -0.35) when compared to those who were not homeless. However, for homeless men with a college education, the odds of accurately reporting cocaine use increases by a factor of 3.36 (b = 1.21) compared to non-homeless men with a college education. For men with a stable residence, educational underachievement did not significantly affect the accuracy of self-reported cocaine use.

Model fit statistics were calculated on all three cocaine models to determine which of the three models best fit the data. For Model 1 the log pseudolikelihood is

⁵ Both interactions were also examined in the same statistical model. However, the standard errors were elevated in the model that included all interaction effects due to the collinearity problems that occurred because the education variable was present in both interactions.

-3032.4833, for Model 2 the log pseudolikelihood is -3030.3424, and for Model 3 the log pseudolikelihood is -3030.3159. The pseudo R² for all three models is 0.07. Since the log pseudolikelihood and pseudo R² were nearly identical in all three models, BIC' scores were calculated for the three models. The likelihood ratio test was not used to determine which model best fit the data since robust standard errors were used and BIC' statistics are not influenced by robust standard errors. The BIC' statistic for Model 1 is -341.711 and -338.666 for Model 2. The BIC' statistic in Models 1 and 2 differed by 3.04, which provides positive support for Model 1 over Model 2. The difference between the BIC' statistic in Model 1 and the BIC' statistic in Model 3 is 0.671. Therefore, there is weak support that Model 3 best fits the data.

Opiate Model

Fewer strain indicators are significant in the opiate models (n = 1,270) than in the cocaine models.⁶ In opiate Model 1, only minority strain and the strain from being in jail for the first time significantly decrease the odds of accurately reporting opiate use as predicted. For blacks, the odds of accurately reporting opiate use decreases by a factor of 0.48 (b = -0.73) compared to whites, holding all other variables constant. In addition, the odds of accurately reporting opiate use for "other minorities" decreases by a factor of 0.45 (b = -0.79) compared to whites, holding all other variables constant. For respondents who had never been to jail before, the odds of accurately reporting opiate use decreases by approximately 47% (OR = 0.53; b = -0.63) compared to respondents who had previously been to jail, holding all other variables constant.

⁶ Refer to Table 7 for the opiate regression models.

	Model 1	(n = 1270)		Model 2	(n = 127	0)
	b	OR	(R.S.E.)	b	OR	(R.S.E.)
Relative Neighborhood Disadvantage ¹	-0.08	0.93	(0.42)	0.14	1.15	(0.52)
Homeless	0.10	1.10	(0.35)	0.33	1.39	(0.49)
Minority Status (White):						
Black	-0.73***	0.48	(0.10)	-0.74***	0.48	(0.10)
Hispanic	-0.26	0.77	(0.24)	-0.24	0.79	(0.24)
Other Minority	-0.79*	0.45	(0.16)	-0.75*	0.47	(0.17)
Educational Underachievement	-0.07	0.93	(0.08)	-0.08	0.93	(0.08)
Employment Status (Employed):			()			
Unemployed	0.11	1.12	(0.17)	0.10	1.11	(0.17)
Other Employment	0.26	1.30	(0.38)	0.25	1.28	(0.36)
Offense Severity (Felony)			· · · ·			· · /
Misdemeanor	-0.39*	0.67	(0.11)	-0.39*	0.68	(0.11)
Traffic/Local Ordinance	-0.96**	0.38	(0.13)	-0.93**	0.39	(0.14)
Offense Charge (Violent)						· · ·
Drug	0.18	1.20	(0.34)	0.20	1.22	(0.35)
Property	0.37	1.44	(0.38)	0.36	1.44	(0.39)
Other	-0.06	0.94	(0.25)	-0.08	0.92	(0.26)
Never Been Arrested Before	-0.56	0.57	(0.17)	-0.58*	0.56	(0.16)
Never Been to Jail Before	-0.63**	0.53	(0.11)	-0.60**	0.55	(0.11)
Age	0.01	1.01	(0.01)	0.01	1.01	(0.01)
Marital Status (Married)			(0101)			(0.00)
Single	0.00	1.00	(0.16)	0.01	1.01	(0.17)
Div/Sep/Wid	-0.39*	0.68	(0.12)	-0.38*	0.68	(0.13)
Hours Since Arrest	0.04	1.04	(0.06)	0.05	1.05	(0.06)
Previous Outpatient Treatment	0.03	1.03	(0.12)	0.04	1.04	(0.12)
nterviewer Age (Same Age As Respondent)						
Older Than Respondent	0.01	1.01	(0.17)	0.00	1.00	(0.17)
Younger Than Respondent	0.05	1.05	(0.20)	0.04	1.04	(0.20)
Female Interviewer	0.02	1.03	(0.19)	0.03	1.03	(0.18)
Different Race Than Interviewer	-0.15	0.86	(0.19)	-0.14	0.87	(0.18)
Quarter (First Quarter)						
Second	0.22	1.24	(0.21)	0.21	1.24	(0.21)
Third	0.22	1.24	(0.21)	0.19	1.21	(0.21)
Fourth	-0.06	0.94	(0.32)	-0.06	0.94	(0.32)
interactions:			(
Relative Neighborhood Disadvantage X Homeless				-4.83**	0.01	(0.01)
Log Pseudolikelihood	-639.1468	4		-636.3512	6	
Pseudo R ²	0.06			0.07		
	10.009			8.055		

Table 7. Regression Estimates for the Accuracy of Self-Reported Opiate Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

In opiate Model 1, arrest severity is the only strain indicator that significantly increases the odds of accurately reporting opiate use. For those arrested for a misdemeanor, the odds of accurately reporting opiate use decreases by a factor of 0.67 (b = -0.39) compared to those arrested for a felony offense. Finally, the odds of accurately reporting opiate use for those arrested for a traffic offense decreases by a factor of 0.38 (b = -0.96) compared to those arrested for a felony offense.

Interaction terms were calculated in the opiate model to determine if accumulated strain also influences the accuracy of self-reported opiate use. Only one interaction effect is significant and is reported in opiate Model 2. For homeless respondents, a one unit increase in relative neighborhood disadvantage decreases the odds of accurately reporting opiate use by 99% (OR = 0.01; b = -4.83) compared to those who were not homeless. However, for those in a stable residence, an increase in relative neighborhood disadvantage does not affect the accuracy of self-reported opiate use. For those who reside in neighborhoods equivalent in disadvantage to the surrounding areas within the county, homelessness does not affect the accuracy of self-reported opiate use. For those who have a stable residence in a neighborhood equivalent in disadvantage to the surrounding areas within the county, the odds of accurately reporting opiate use decreases by a factor of 0.56 (b = -0.58).

Model fit statistics were subsequently calculated on the two opiate models to determine which model best fits the data. Model 1 had a log pseudolikelihood of -639.14684 and a pseudo R^2 of 0.06, while Model 2 had a log pseudolikelihood of -636.35126 and a pseudo R^2 of 0.07, which indicates Model 2 best fits the data. To further determine the strength of support for Model 2 over Model 1, BIC' statistics were

calculated for both models. The difference in the BIC' statistic between the two models was 1.954, which provides weak support for Model 2 over Model 1.

Methamphetamine Model

In methamphetamine Model 1 (n = 2,308), minority strain, strain from the seriousness of the arrest charge, and the strain from being in jail for the first time all significantly affect the accuracy of self-reported methamphetamine use in the predicted direction.⁷ For black respondents, the odds of accurately reporting methamphetamine use decreases by a factor of 0.40 (b = -0.92) when compared to white respondents. In addition, the odds for Hispanic respondents accurately reporting methamphetamine use decreases by a factor of 0.57 (b = -0.56) when compared to white respondents. Those arrested for a drug offense, property offense, and "other" type of offense were all more likely to accurately report methamphetamine use than those arrested for a violent offense. For those who had never been to jail before, the odds of accurately reporting methamphetamine use decreases by a factor of 0.64 (b = -0.45) compared to those who had previously been to jail, holding all other variables constant.

Many strain variables in Model 1, however, are also significant in the opposite direction then predicted in the methamphetamine model. For the homeless, the odds of accurately reporting methamphetamine use increases by a factor of 1.59 (b = 0.47) when compared to those who reported living in a stable residence. In addition, for the unemployed, the odds of accurately reporting methamphetamine use increases by a factor of 1.65 (b = 0.50) when compared to employed respondents. Finally, those arrested for a

⁷ Refer to Table 8 for the methamphetamine regression models.

aite Neighborhood Disadvantage ¹ 0.08 1.08 (0.29) 1.05 (0.29) ority Status (White): 0.47** 1.59 (0.29) 1.09*** 2.97 (0.81) Black -0.92*** 0.40 (0.10) -0.91*** 0.40 (0.10) Black -0.92*** 0.47 (0.10) -0.91*** 0.40 (0.10) User Status (White): -0.56*** 0.57 (0.08) -0.56*** 0.57 (0.08) Other Minority -0.39 0.67 (0.14) -0.40 0.67 (0.17) User Biophysic -0.11 0.90 (0.07) -0.07 0.93 (0.07) User Biophysic -0.5 0.61 (0.05) -0.51*** 0.61 (0.05) Taffic/Local Ordinance -0.69* 0.50 (0.16) 0.54*** 0.61 (0.25) 0.48*** 1.62 (0.29) Other -0.49*** 1.62 (0.25) 0.48*** 1.62 (0.25) 0.49*** 1.64 (0.26) Other -0.13 0.46*** 1.62 (0.25) 0.49*		Model 1			Model 2	(n = 230	8)
beles0.47**1.590.0290.09**2.970.081Ny Status (White): Hispanic0.92***0.40(0.10)-0.91***0.40(0.10)Hispanic0.56***0.57(0.08)-0.56***0.57(0.08)Other Minority-0.390.67(0.14)-0.400.67(0.14)Jayment Status (Employed):0.070.010-0.180.840.20Usemployed0.50***1.55(0.16)-0.180.840.20Other Employement0.50***1.61(0.05)-0.180.450.16Status (Employed)0.47**1.62(0.16)-0.69**0.500.16Status (Employement0.49***0.51(0.16)-0.69**0.50**0.16Status (Envloyement0.49***1.60(0.25)0.48**1.62(0.25)Status (Envloyement0.47***1.60(0.25)0.48**1.62(0.26)Diverse Vision0.47***1.60(0.11)-0.65***0.61(0.02)Diverse Vision0.610.010.010.010.010.01Diverse Vision0.62***1.61(0.25)0.48**1.62(0.25)Other0.47***1.62(0.21)0.61(0.02)0.010.01Diverse Vision0.610.010.010.010.010.01Status (Marrie)0.050.12*0.05*0.12*0.050.13Single Single Single S		b	OR	(R.S.E.)	b	OR	(R.S.E)
ofty State (White): 0.92*** 0.40 0.10 Black 0.95*** 0.57 (0.08) 0.56*** 0.57 (0.08) Other Minority 0.39 0.67 (0.14) 0.40 0.01 0.08 Other Minority 0.39 0.67 (0.14) 0.40 0.67 (0.14) cational Inderachie venent 0.50*** 1.65 (0.16) 0.51*** 1.66 (0.17) Other Employnent 0.15 0.86 (0.20) 0.18 80.44 (0.20) miss Severity (Felony)	Relative Neighborhood Disadvantage ¹	0.08	1.08	(0.28)	0.05	1.05	(0.28)
Black Hipmine Other Minority0.92*** 0.92***0.40 0.0080.91*** 0.95***0.40 0.08 0.08 0.070.10 0.08 0.07Other Minority Logenditivement Umenployed Other Katus (Employod):0.71 0.070.700.700.710.70Umenployed Other Employment Taffiel-Cael Ordinance Angent Taffiel-Cael Ordinance Other Employment0.50*** 0.50***1.61 0.050***0.51*** 0.61 0.050***0.61 0.05****0.51*** 0.61 0.05****0.61 0.05****0.61 0.05***********************************	Homeless	0.47**	1.59	(0.29)	1.09***	2.97	(0.81)
Hispanic 0.56*** 0.57 (0.08) 0.56**** 0.57 (0.08) Other Minoriy 0.31 0.30 (0.07) 0.40 0.67 (0.14) cational Underachievenent 0.11 0.90 (0.07) 0.51 0.64 (0.17) oppend Status (Employed) 0.50*** 1.65 (0.16) 0.51*** 0.64 (0.20) Other Employment 0.69** 0.50 0.616 0.51*** 0.61 (0.59) mess Severity (Folony) -0.69* 0.50 0.616 0.69** 1.87 (0.25) mess Severity (Folony) -0.69* 1.62 (0.25) 0.49*** 1.62 (0.25) mess Severity (Folony) -0.64*** 1.62 (0.25) 0.49*** 1.62 (0.25) mess Severity (Folony) -0.64*** 1.62 (0.25) 0.49*** 1.62 (0.25) mess Severity (Folony) -0.64**** 1.62 (0.25) 0.49*** 1.64 (0.15) Severity (Folony) -0.64	Minority Status (White):						
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Other Minority-0.390.670.14-0.400.670.14caloral UderAnchievement-0.110.020.000.070.030.07logment Status (Employed):-0.150.660.20-0.180.840.20umenployed-0.150.660.05-0.180.840.20nase Severity (Felony)-0.49**0.610.05-0.19**0.610.05Taffic Local Ondinance-0.49**0.610.05-0.59**0.610.05Taffic Local Ondinance-0.49**1.670.280.63***1.870.29Progenty0.47**1.600.280.63***1.870.29Other Elsen Arrested Before0.150.840.110.45**0.640.15e Been Arrested Before0.950.110.011.010.01ital Status (Married)-0.50.950.120.050.12Since Arrest0.01*1.140.060.11*1.110.06iso Since Arrest0.050.95*0.130.150.05*0.15iso Since Arrest0.071.070.150.36*1.050.08outpatient Treatment0.070.080.060.190.01iso Since Arrest0.010.010.060.16*0.05outpatient Treatment0.070.080.080.090.01iso Since Arrest0.010.010.060.160.01iso Sin	Hispanic	-0.56***	0.57	(0.08)	-0.56***	0.57	(0.08)
$ \begin{array}{ $		-0.39	0.67	(0.14)	-0.40	0.67	(0.14)
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hale Interviewer -0.15 0.86 (0.08) -0.15 0.86 (0.09) erent Race Than Interviewer -0.08 0.92 (0.08) -0.07 0.93 (0.09) rter (First Quarter) - - - - - - - - 0.01 - 0.00 1.00 (0.16) - 0.01 - 0.03 - 0.01 1.01 (0.11) 0.00 1.00 (0.11) - 0.05 0.28 1.32 (0.55) -							
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$\begin{array}{cccccccccccccccccccccccccccccccccccc$		0.01	1.01	(0.16)	0.00	1.00	(0.16)
Fourth 0.30 1.35 0.56 0.28 1.32 (0.55) ractions: -0.55** 0.58 (0.10) pseudolikelihood -1367.5127 -1365.1342 udo R ² 0.07 0.07							
ractions: neless X Educational Underachievement -0.55** 0.58 (0.10) Pseudolikelihood -1367.5127 -1365.1342 ndo R ² 0.07 0.07							
-0.55** 0.58 (0.10) Pseudolikelihood -1367.5127 -1365.1342 udo R ² 0.07 0.07	nteractions:	0.50	1.00	(0.00)	0.20		()
1do R ² 0.07 0.07	Iomeless X Educational Underachievement				-0.55**	0.58	(0.10)
1do R ² 0.07 0.07	log Pseudolikelihood	-1367.512	7		-1365.134	2	
	Pseudo R^2						
	BIC'						
		-118.770			-123.335		

Table 8. Regression Estimates for the Accuracy of Self-Reported Methamphetamine Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

misdemeanor or traffic/local ordinance were statistically more likely to accurately report methamphetamine use than those arrested for a felony. Another important finding is those that had previously been enrolled in an outpatient substance abuse program were more likely to accurately report methamphetamine use than those that had never enrolled in a substance abuse treatment program.

Accumulated strain is examined in the methamphetamine model by introducing interactions between the five main strain variables. The only interaction that significantly influences the accuracy of self-reported methamphetamine use is between homelessness and educational underachievement and is included in Model 2. For the homeless, a one unit increase in educational underachievement decreases the odds of accurately reporting methamphetamine use by a factor of 0.58 (b = -0.55). However, for those with a stable residence, educational underachievement does not significantly affect the odds of accurately reporting methamphetamine use. In addition, for those with a college education, homelessness does not statistically affect the odds of accurately reporting methamphetamine use.

Log pseudolikelihood, pseudo R^2 , and BIC' statistics were calculated to determine which methamphetamine model best fits the data. Model 1 had a log pseudolikelihood of -1367.5127 and a pseudo R^2 of 0.07, while Model 2 had a log pseudolikelihood score of -1365.1342 and a pseudo R^2 of 0.07. BIC' statistics were calculated to determine which model best fit the data since the log pseudolikelihood and the pseudo R^2 were similar in both models. The difference between the BIC' statistic in Model 1 and Model 2 was 4.757, which indicates modest support for Model 2 of the methamphetamine models.

Marijuana Model

In the marijuana model (n = 7,485), minority strain, strain from the seriousness of the arrest charge, and strain from being arrested and in jail for the first time all significantly affect the accuracy of self-reported marijuana use in the direction predicted.⁸ For Hispanic respondents, the odds of accurately reporting marijuana use decreases by a factor of 0.73 (b = -0.32) compared to white respondents. The odds of accurately reporting marijuana use are 72.2% (b = 0.54) greater for those arrested for a drug offense compared to those arrested for a violent offense. For respondents who had never been arrested before, the odds of accurately reporting marijuana use decreases by a factor of 0.75 (b = -0.29) compared to respondents who had previously been arrested. In addition, the odds of accurately reporting marijuana use for respondents who had never been to jail before decreases by a factor of 0.70 (b = -0.36) compared to respondents who had previously been to jail.

Other important characteristics that significantly affect the accuracy of selfreported marijuana use are the age of the respondent and whether the respondent had previously been in an outpatient substance abuse treatment program. For each additional year in age, the odds of accurately reporting marijuana use decreases by 3% (OR=.97; b = -0.03), holding all other variables constant. The odds of accurately reporting marijuana use increases by approximately 31% (b = 0.27) for respondents who had previously been in an outpatient substance abuse treatment program compared to respondents who have never been in such a program. No interaction effects significantly influence the accuracy of self-reported marijuana use.

⁸ Refer to Table 9 for the marijuana regression model.

Model 1	(n = 7485)	
b	OR	(R.S.E.)
0.08	1.08	(0.21)
0.23	1.26	(0.22)
-0.19	0.83	(0.08)
-0.32**	0.73	(0.08)
-0.25	0.78	(0.13)
-0.05	0.95	(0.04)
0.11	1.11	(0.08)
		(0.09)
-0.04	0.96	(0.06)
		(0.12)
0.17	0.05	(0.12)
0 54***	1 72	(0.19)
		(0.14)
		(0.10)
		(0.07)
		(0.06)
		(0.00)
-0.03	0.97	(0.00)
0.15	1.17	(0.10)
		(0.10)
		(0.10) (0.03)
0.27*	1.51	(0.14)
0.01	0.00	(0.10)
		(0.10)
		(0.09)
		(0.13)
-0.02	0.98	(0.08)
		(0.10)
		(0.08)
-0.23*	0.79	(0.08)
-3308.926		
0.03		
	0.08 0.23 -0.19 -0.32** -0.25 -0.05 0.11 -0.12 -0.04 -0.19 0.54*** 0.20 0.11 -0.29*** -0.36*** -0.03*** 0.15 0.14 0.01 0.27* -0.01 0.07 0.03 -0.02 0.06 -0.05 -0.23*	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table 9. Regression Estimates for the Accuracy of Self-Reported Marijuana Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p-0.001 ** p<0.01 * p<0.05</p>

Benzodiazepine Model

In the benzodiazepine model (n = 724), minority status is the only strain indicator that affects the accuracy of self-reported benzodiazepine use in the predicted direction.⁹ For black respondents, the odds of accurately reporting benzodiazepine use decreases by a factor of 0.47 (b = -0.75) when compared to white respondents. There appears to be no strain indicator that significantly increases the odds of accurately reporting benzodiazepine use. However, several personal attributes did significantly affect the odds of accurately reporting benzodiazepine use. For every additional year in age, the odds of accurately reporting benzodiazepine use decreases by 3% (OR=.97; b = -0.03), holding all other variables constant. In addition, the odds of accurately reporting benzodiazepine use increases by approximately 73% (b = 0.55) for respondents who had previously been in an outpatient substance abuse treatment compared to respondents who had never been to such a program. No interaction effects significantly influenced the accuracy of self-reported benzodiazepine use.

Methadone Model

In methadone Model 1 (n = 209), no strain indicator significantly affects the accuracy of self-reported methadone use.¹⁰ The only variable in Model 1 that influences the accuracy of self-reported methadone use is previous enrollment in an outpatient substance abuse treatment program. The odds of accurately reporting methadone use increases by approximately 128% (b = 0.83) for respondents who had previously been in

⁹ Refer to Table 10 for the benzodiazepine regression model.

¹⁰ Refer to Table 11 for the methadone regression models.

	Model 1	(n = 724)	
	b	OR	(R.S.E.)
Relative Neighborhood Disadvantage ¹	-0.25	0.78	(0.42)
Homeless	-0.62	0.54	(0.21)
Minority Status (White):			
Black	-0.75***	0.47	(0.11)
Hispanic	-0.48	0.62	(0.19)
Other Minority	-0.40	0.67	(0.27)
Educational Underachievement	-0.12	0.89	(0.10)
Employment Status (Employed):			
Unemployed	0.29	1.34	(0.26)
Other Employment	0.75***	2.12	(0.48)
Offense Severity (Felony)			
Misdemeanor	-0.12	0.88	(0.15)
Traffic/Local Ordinance	-0.22	0.80	(0.35)
Offense Charge (Violent)	0.22		()
Drug	0.50	1.64	(0.53)
Property	0.39	1.47	(0.00)
Other	0.30	1.35	(0.10) (0.42)
Never Been Arrested Before	-0.26	0.77	(0.7)
Never Been to Jail Before	0.12	1.13	(0.27)
Age	-0.03**	0.97	(0.2) (0.01)
Marital Status (Married)	-0.05	0.77	(0.01)
Single	-0.55**	0.58	(0.12)
Div/Sep/Wid	-0.74***	0.48	(0.12) (0.11)
Hours Since Arrest	0.06	1.06	(0.11) (0.10)
Previous Outpatient Treatment	0.55**	1.73	(0.10)
Interviewer Age (Same Age As Respondent)	0.55	1.75	(0.55)
Older Than Respondent	-0.51**	0.60	(0.12)
Younger Than Respondent	0.05	1.05	(0.23)
Female Interviewer	0.32	1.38	(0.26)
Different Race Than Interviewer	-0.00	1.00	(0.20)
Quarter (First Quarter)	0.07	0.77	(0.19)
Second	-0.27	0.77	(0.18)
Third	0.12	1.12	(0.33)
Fourth	0.49	1.64	(0.61)
Interactions:			
No Interactions Present			
Log Pseudolikelihood	-376.45482	2	
Pseudo R^2	0.08		

Table 10. Regression Estimates for the Accurac	v of Self-Reported Benzodiazepine	Use Among Predictors of Strain.	Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

Table 11. Regression Estimates for the Accuracy of Self-Reported Methadone Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

	Model 1	(n = 209)		Model 2	(n = 209)	
	b	OR	(R.S.E.)	b	OR	(R.S.E)
tive Neighborhood Disadvantage ¹	0.03	1.03	(0.67)	0.64	1.90	(1.35)
eless	0.49	1.63	(1.18)	0.97	2.63	(1.75)
prity Status (White):						
Black	-0.92	0.40	(0.22)	-1.08	0.34	(0.21)
Hispanic	0.31	1.36	(0.61)	0.30	1.35	(0.66)
Other Minority	0.47	1.61	(1.02)	0.46	1.59	(1.03)
cational Underachievement	-0.09	0.92	(0.21)	-0.15	0.86	(0.21)
loyment Status (Employed):						· /
Unemployed	-0.27	0.76	(0.30)	-0.24	0.79	(0.31)
Other Employment	0.90	2.46	(1.79)	1.02	2.78	(1.93)
nse Severity (Felony)						
Misdemeanor	-0.29	0.75	(0.37)	-0.28	0.76	(0.38)
Traffic/Local Ordinance	-0.61	0.54	(0.34)	-0.67	0.51	(0.31)
nse Charge (Violent)			. /			
Drug	1.07	2.92	(1.99)	1.08	2.96	(2.08)
Property	0.78	2.18	(1.22)	0.68	1.97	(1.17)
Other	0.57	1.78	(1.08)	0.50	1.64	(1.04)
er Been Arrested Before	-1.56	0.21	(0.21)	-1.71	0.18	(0.20)
er Been to Jail Before	0.67	1.95	(1.26)	0.79	2.20	(1.56)
	0.01	1.01	(0.03)	0.01	1.01	(0.03)
al Status (Married)			(0.00)	0.01		(0100)
Single	0.61	1.84	(1.13)	0.67	1.96	(1.23)
Div/Sep/Wid	0.37	1.45	(0.52)	0.49	1.63	(0.55)
s Since Arrest	-0.19	0.83	(0.18)	-0.21	0.81	(0.17)
ous Outpatient Treatment	0.83**	2.28	(0.70)	0.77*	2.16	(0.68)
viewer Age (Same Age As Respondent)	0.00	2.20	(0.77	2.10	(
Older Than Respondent	0.29	1.34	(0.80)	0.31	1.37	(0.82)
Younger Than Respondent	0.29	1.34	(0.66)	0.25	1.29	(0.64)
ale Interviewer	-0.39	0.68	(0.29)	-0.38	0.68	(0.32)
erent Race Than Interviewer	0.08	1.09	(0.35)	0.17	1.18	(0.44)
ter (First Quarter)			· · · /			. /
Second	-0.20	0.82	(0.59)	-0.17	0.85	(0.63)
Third	-0.18	0.83	(0.44)	-0.18	0.83	(0.44)
Fourth	-0.28	0.76	(0.52)	-0.38	0.69	(0.47)
actions:						
tive Neighborhood Disadvantage X Homeless				-4.63*	0.01	(0.02)
						. /
Pseudolikelihood	-84.07264	1		-83.05919	5	
do R^2	0.16			0.17		
	45.985			43.958		

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

an outpatient substance abuse treatment program compared to respondents who had never been in an outpatient substance abuse treatment program.

Although no single strain predictor affected the accuracy of self-reported methadone use, a type of accumulated strain does significantly influence the accuracy of self-reported methadone use and is included in Model 2. For those who were homeless, a one unit increase in relative neighborhood disadvantage decreases the odds of accurately reporting methadone use by 99% (OR=.01; b = -4.63) compared to those who were not homeless.

Log pseudolikelihood, pseudo R^2 , and BIC' statistics were calculated to determine which methadone model best fit the data. The log pseudolikelihood for Model 1 is -84.07261 and the pseudo R^2 is 0.16. The log pseudolikelihood for Model 2 is -83.059195 and the pseudo R^2 is 0.17. Since the log pseudolikelihood and the pseudo R^2 were similar in both models, BIC' statistics were calculated. The BIC' statistic for Model 1 is 45.985 and the BIC' statistic for Model 2 is 43.958. Therefore, the difference between the scores is 2.027, which indicates that there is modest support for Model 2 being a better fit than Model 1.

Alcohol Model

For the alcohol model (n = 1,057), only minority strain and the seriousness of the arrest charge significantly affects the accuracy of self-reported alcohol use in the predicted direction. ¹¹ For black respondents, the accuracy of self-reported alcohol use decreases by a factor of 0.41 (b = -0.89) when compared to white respondents. In addition, the accuracy of self-reported alcohol use for Hispanics decreases by a factor of

¹¹ Refer to Table 12 for the alcohol regression model.

	Model 1	(n = 1057	7)	
	b	OR	(R.S.E.)	
Relative Neighborhood Disadvantage ¹	-0.28	0.76	(0.48)	
Homeless	0.76	2.13	(1.03)	
Minority Status (White):				
Black	-0.89**	0.41	(0.12)	
Hispanic	-1.00***	0.37	(0.11)	
Other Minority	-0.52	0.59	(0.23)	
Educational Underachievement	0.23	1.26	(0.16)	
Employment Status (Employed):				
Unemployed	0.42*	1.52	(0.32)	
Other Employment	0.74*	2.10	(0.80)	
Offense Severity (Felony)				
Misdemeanor	0.26	1.29	(0.28)	
Traffic/Local Ordinance	-0.18	0.84	(0.35)	
Offense Charge (Violent)				
Drug	0.21	1.24	(0.23)	
Property	0.57	1.76	(0.53)	
Other	0.42*	1.52	(0.28)	
Never Been Arrested Before	0.20	1.22	(0.34)	
Never Been to Jail Before	-0.44	0.65	(0.15)	
Age	-0.03*	0.97	(0.01)	
Marital Status (Married)				
Single	-0.12	0.89	(0.25)	
Div/Sep/Wid	-0.04	0.96	(0.29)	
Hours Since Arrest	-0.12	0.88	(0.09)	
Previous Outpatient Treatment	0.70**	2.01	(0.54)	
Interviewer Age (Same Age As Respondent)				
Older Than Respondent	-0.62*	0.54	(0.16)	
Younger Than Respondent	0.07	1.07	(0.24)	
Female Interviewer	0.17	1.18	(0.28)	
Different Race Than Interviewer	-0.04	0.96	(0.22)	
Quarter (First Quarter)				
Second	0.15	1.16	(0.19)	
Third	0.25	1.29	(0.31)	
Fourth	-0.05	0.95	(0.42)	
Interactions:				
No Interactions Present				
Log Pseudolikelihood	-350.03054	4		
Pseudo R^2	0.08			

Table 12. Regression Estimates for the Accuracy of Self-Reported Alcohol Use Among Predictors of Strain, Personal Attributes, and Interviewer Characteristics

¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage *** p<0.001 ** p<0.01 * p<0.05</p>

0.37 (b = -1.00) when compared to white respondents. For respondents who were arrested for an "other" type of offense, the odds of accurately reporting alcohol use increases by a factor of 1.52 (b = 0.42) when compared to respondents arrested for a violent offense, holding all other variables constant.

The only indicator of strain that significantly affects the accuracy of self-reported alcohol use in the opposite direction than predicted is unemployment. The odds of accurately reporting alcohol use for respondents who were currently unemployed increases by a factor of 1.52 (b = 0.42) compared to respondents who were currently employed, holding all other variables constant. Other notable findings that affect the accuracy of self-reported alcohol use include the age of the respondent and previous enrollment in an outpatient substance abuse treatment program. For each additional year in age, the odds of accurately reporting alcohol use increases by a proximately 100% (b = -0.03). For those who had previously enrolled in an outpatient substance abuse program, the odds of accurately reporting alcohol use increases by approximately 100% (b = 0.70) compared to respondents who had never enrolled in an outpatient substance abuse treatment program. No significant interactions in the alcohol model are present.

Diagnostics

Multicollinearity and heteroskedasticity were examined for each of the seven models. To check for multicollinearity, the variance inflation factor (VIF) was calculated for each independent variable.¹² Most VIF scores were below 2.00. Only "other offense," age, and "interviewer is older" were slightly above 2.00. Therefore,

¹² Refer to Appendix B for a list of VIF scores.

multicollinearity was not a problem. However, due to fixed effects, some cities were dropped due to collinearity problems within the particular city. No cities were dropped from the cocaine and marijuana model. One city (2 observations) was dropped from the opiate model while one city (28 observations) was dropped from the alcohol model. Two cities (2 observations) were dropped from the benzodiazepine model. Eight cities (24 observations) were dropped from the methamphetamine model and eight cities (20 observations) were dropped from the methadone model.

To check for heteroskedasticity within the seven models, each model was calculated with and without robust standard errors. Every model except the methadone model slightly varied on the number of statistical findings. Mild heteroskedasticity is present in six of the seven models. Therefore, robust standard errors were used on all models including the methadone model to protect against heteroskedasticity and for conformity between the seven models.

The results of the seven drug models suggest that strain influences the accuracy of self-reported drug use. However, these results vary between drug models. Why these differences vary across models, implications of the current study, and directions for future research are discussed in Chapter 5.

Chapter Five

Conclusions

The main purpose of this study was to determine if strain decreased the accuracy of self-reported drug use across seven different types of drugs. The analyses reveal that multiple types of strain significantly decrease the odds of accurately reporting drug use in all drug models. However, each drug model varies in the types of strain associated with inaccurate self-reported drug use. Prior literature has indicated that the predictors of accurate self-reported drug use vary by drug type based on the stigma associated with the different types of substances (Lu et al., 2001; Magura and Kang, 1996; Rosay et al., 2007). The one-way ANOVA conducted in this study indicates that the differences in predictors across drug groups may also be the result of relatively distinct populations testing positive for each type of drug. For example, the predictors for the cocaine model differ from those in the alcohol model since these two models were composed of two relatively distinct subsamples.

Table 13 presents a summary of the effects of strain on the accuracy of selfreported drug use across the seven drug models. Across the seven drug models, the most influential source of strain is being of minority status. In six of the seven drug models, being a minority significantly decreases the odds of the respondent accurately reporting drug use. In four of the seven models, being arrested for a violent offense significantly decreased the odds of accurately reporting drug use. In two of the drug models, strain from never having been arrested before decreases the odds of accurately reporting drug use, while never having been to jail decreases the odds of accurately reporting drug use in

	Cocaine (n = 4935)	Opiates $(n = 1272)$	Methamphetamines $(n = 2332)$	Marijuana (n = 7485)	Benzodiazepines $(n = 726)$	Methadone $(n = 229)$	$\begin{array}{l} Alcohol\\ (n=1085) \end{array}$
Relative Nghd. Disadvantage ¹	ns	ns	ns	ns	ns	ns	ns
Homeless	+	ns	+	ns	ns	ns	ns
Minority Status:							
Black	-	-	-	ns	-	ns	-
Hispanic	ns	ns	-	-	ns	ns	-
Other Minority	ns	-	ns	ns	ns	ns	ns
Educational Underachievement	-	ns	ns	ns	ns	ns	ns
Unemployed	+	ns	+	ns	ns	ns	ns
Felony Offense (vs. Misdemeanor)	+	+	+	ns	ns	ns	ns
Violent Offense (vs. Drug Offense)	-	ns	-	-	ns	ns	ns
Never Been Arrested Before	ns	-	ns	-	ns	ns	ns
Never Been to Jail Before	ns	-	-	-	ns	ns	ns
Previous Outpatient Treatment	+	ns	+	+	+	+	+
Interactions:							
Educational Underachievement							
X Unemployed	-	ns	ns	ns	ns	ns	ns
Homeless X Educational							
Underachievement	-	ns	-	ns	ns	ns	ns
Relative Nghd Dis. X Homeless	ns	-	ns	ns	ns	-	ns

Table 13. Influence of Strain on the Accuracy of Self-Reported Drug Use Across Seven Types of Drugs

 ¹Relative Neighborhood Disadvantage created by dividing Neighborhood Disadvantage by County Disadvantage

 +
 Significant positive relationship with accurate self-reported drug use

 Significant negative relationship with accurate self-reported drug use

Not significantly related to the accuracy of self-reported drug use ns

three of the seven drug models. Finally, less education (higher educational underachievement) significantly decreases the odds of accurately reporting drug use in one of the seven drug models. Therefore, strain experienced as a result of being a minority, being arrested for a violent offense, never having been arrested nor having been to jail before, and having a higher educational underachievement all significantly decreases the odds of accurately reporting drug use.

In contrast to predictions made in this study in regard to general strain theory, the strain indicators that significantly increase the odds of accurately reporting drug use across the seven drug models include homelessness, unemployment, and the seriousness of the charge. Being homeless or unemployed increases the odds of accurately reporting drug use in both the cocaine and methamphetamine models. Being arrested for a felony increases the odds of accurately reporting drug use for the cocaine, opiate, and methamphetamine models.

However, many of the strain indicators that were originally found to increase the accuracy of self-reported drug use, showed an inverse relationship when interaction effects were examined. This finding is in line with Agnew's (2001) general strain theory. Specifically, homelessness significantly decreases the accuracy of self-reported drug use for those who had higher educational underachievement in both the cocaine and methamphetamine models. In the cocaine model, those who were unemployed and had higher educational underachievement were also less likely to accurately report drug use. For both the opiate and methadone models, respondents who were homeless and resided in a neighborhood with more disadvantage than those areas in the surrounding county, were less likely to accurately report drug use.

The only strain indicator that remained significant in the opposite direction predicted is the severity of the offense. It is unknown why those who were arrested for a felony offense would be more likely to accurately report drug use than those arrested for a misdemeanor. However, one possible reason could be the coding of the data. As mentioned earlier, the current study only includes the most serious recent charge. It could be that respondents who were arrested for three misdemeanors were under more strain than respondents who were arrested for one felony.

Another finding of note, although not directly related to general strain theory, is that prior enrollment in a substance abuse treatment program significantly increases the odds of accurately reporting drug use in six of the seven drug models. This finding has been noted in prior literature (Magura and Kang, 1996). For those who previously took part in substance abuse treatment, admitting to drug use may not contribute to the individual's anticipated strain. This may be because these individuals have previously admitted to the use of drugs in order to obtain substance abuse treatment.

Theoretical Contributions

The current study found no support for non-intentional framework of test adequacy since the accuracy of self-reported drug use varied from approximately 45% in the cocaine model to nearly 85% in the alcohol model. If the accuracy of the urinalysis test itself solely affected the findings, then fewer than 3% of the respondents in each model would have inaccurately reported drug use. The current study found little, clear support for the non-intentional cognitive framework since several respondents were able to recall they had consumed a drug but were unable to identify the type of drug they consumed. This was apparent with the question "what other type of drug have you used in the past 72 hours." Many respondents reported that they had not consumed opiates or benzodiazepines but listed types of opiates and benzodiazepines for this question. To find overwhelming support for a cognitive framework (i.e., memory errors), the current study would have to have found high and similar accuracy rates for all seven different types of drugs. The current study also found support for the social desirability thesis since the more stigmatized drugs were less accurately reported than the less stigmatized drugs. However, the social desirability thesis was unable to forecast the predictors associated with inaccurate self-reported drug use because it is unknown what in fact is considered undesirable across varying individuals. The current study did find support for Agnew's (2001) general strain theory. Strain and the interactions between the different types of strain decreased the odds of accurately reporting drug use.

The general strain theory literature has often concentrated on criminal coping, or illegal/deviant reactions to strain. This study suggests that deviant coping mechanisms should include purposeful deception. In these analyses, respondents appeared to try to prevent experiencing further strain by altering their responses to appear more favorable to them, in light of their current situation. Therefore, this study extends general strain theory by incorporating purposeful deception as an additional deviant coping mechanism in response to strain.

This study also adds to the limited research on anticipated strain. In the current study, the number of strains significantly related to inaccurate self-reported drug use increases with the associated stigma of the drug. For example, few indicators of strain are significant in the marijuana and alcohol models compared to the cocaine, opiate, and

methamphetamine models - substances generally associated with higher levels of stigma. This indicates that the anticipated strain of admitting to drug use in general, coupled with the respondent's current levels of strain, were severe enough to alter the respondent's responses about drug use. It appears this deception allowed respondents to avoid the future anticipated strains of becoming further stigmatized in the criminal justice system as a drug user, or to prevent additional drug-related criminal charges or increased surveillance.

Policy Recommendations

In addition to theoretical contributions, the current study also suggests support for several policy recommendations. When attempting to identify active substance abuse users, criminal justice agencies should seek information about the individual's current level of strain. This would allow the professionals in the criminal justice system to provide more adequate referrals to substance abuse treatment programs. Increasing the precision of accuracy rates would also decrease the criminal justice system's reliance on the use of urinalyses and increase reliance on self-reported drug use. This would save revenue and could subsequently increase the availability of treatment for those currently in the custody of the criminal justice system.

Inquiring about the individual's current level of strain may increase the precision and accuracy rates for self-reported drug use and may also be incorporated into actuarial methods of measuring the individual's risks and needs. Therefore, inquiring about current levels of strain could also assist criminal justice professionals in identifying other individuals who might be less than truthful about other types of sensitive information.

For example, an individual may not admit to anger management problems, however, with knowledge of strain predictors, criminal justice workers may also be able to provide better referrals for those suffering from anger management problems.

Increasing the accuracy of self-reported drug use also minimizes the intrusiveness of the criminal justice system into an individual's privacy. Obtaining a urinalysis specimen can cause additional stress to the respondent by placing the individual in an uncomfortable and demeaning situation (i.e., providing a urine specimen in the presence of others). Increasing the use of self-reported measures as opposed to conducting multiple urinalyses over time may enhance the rapport between those involved in the criminal justice system and the professionals who work with these individuals.

Limitations and Implications for Future Research

As mentioned in the introduction, the current study is not generalizable to all inmates in jails nationwide. In addition, the current study did not include data on females or juveniles; therefore, generalizations cannot be made about these unique populations. Future research should examine the relationship between strain and the accuracy of selfreported drug use using samples of females or juvenile arrestees. Research using different samples may help determine if strain indicators have varying effects on respondents based on sex or being a minor.

As mentioned earlier, operationalization of the various types of strain is a limitation in that all measures of strain used in this study are objective instead of subjective. In addition, the operationalizations of many of the types of strain in the current study have not been used in prior tests of general strain theory. For example,

minority status and educational underachievement are not commonly used as indicators of strain in prior tests of general strain theory. Future research that explores congruency rates of self-reports should focus on subjective strain. For example, instead of asking if the respondent is a minority, and then assuming that everyone who is a minority experiences greater levels of strain, the interviewer should inquire specifically about the types and levels of stressors the individual experiences due to being a minority.

Another limitation in the current study was its inability to differentiate between cocaine and crack-cocaine. Crack-cocaine is more stigmatized then cocaine and the accuracy rates between the two types of drugs should substantially differ (Lu et al., 2001). For example, by combining cocaine with crack-cocaine, it is unknown if the predictors of accurate self-reported cocaine use differ from the predictors of accurate self-reported cocaine use differ from the predictors of accurate self-reported crack-cocaine use. Therefore, future studies should seek to parse out these differences to determine if strain is still a significant predictor of self-reported drug use within the subgroups of both crack-cocaine users and cocaine users. The current study was also unable to differentiate between heroin and other types of opiates; future studies should also examine these differences.

Another limitation in the current study occurred as a result of the differences in time frames that occurred between the drugs' window of detection and the corresponding lengths of time in the self-report measures. One of the largest discrepancies existed in the benzodiazepine model (14-day window of detection; 72 hour self-report measure) which was one of the lowest accurately reported drugs. Therefore, all respondents who used between four and fourteen days prior to the study accurately underreported benzodiazepine use. In addition, the length of time in the self-report measure in the

alcohol and marijuana models asked about use within the last 30 days, whereas, all other substances included measures representing use in the last 72 hours. Marijuana use can be detected 30 days after use; therefore, a self-report period of 30 days for marijuana aligns with marijuana's window of detection. However, a self-report period of 30 days for the alcohol model does not align with alcohol's window of detection. The discrepancy between length of time of the self-report measure and the window of detection for alcohol use is larger than the discrepancy found in the benzodiazepine model. Since length of time for the self-report measure is larger than the window of detection for alcohol, the alcohol model did not incorporate any additional accurate under-reporters. However, a longer self-report period for alcohol and marijuana may reduce the anticipated strain of admitting to recent use of these drugs and may artificially increase the accuracy of selfreported drug use for alcohol and marijuana. Future studies should attempt to keep the time frames as similar as possible when examining accuracy rates and predictors of these accuracy rates.

The last major limitation of the current study is its inability to test for other applicable theories. It is possible that those with less social control mechanisms in their lives or those with lower self control are less likely to accurately report drug use. It may also be that deception is a learned response from association with intimate contacts, such as social learning theory would predict. Future research should strive to include variables for these additional theories. This would greatly expand the applicability of other criminological theories and would help determine if the current findings are robust.

Implications for researchers include incorporating strain related measures when examining self-reports of highly sensitive issues. Past literature indicates that highly sensitive topics are not reported as accurately as less sensitive topics (Harrison, 1997; Thornberry and Krohn, 2000). Several methods have been introduced in recent years that increase the accuracy of self-report measures such as Computer-Assisted Personal Interview (CAPI) or randomized response techniques (Thornberry and Krohn, 2000). However, these techniques can be costly and time consuming compared to asking the individual about his or her current levels of strain. If anticipated strain reduces the accuracy of self-reported sensitive items, then strain can be included as a control variable or as a frequency weight.

With the war on drugs and the U.S. policies of mass imprisonment, drug users have experienced greater surveillance and control by the criminal justice system than in the past. Many individuals may choose to deceive criminal justice professionals about their drug use and involvement. However, general strain theory offers a new way to assess people who may be less than truthful about their drug use, and perhaps other stigmatized and sensitive issues.

Appendix A

ADAM Cities:

Albuquerque Anchorage Atlanta Birmingham Boston Capital Area New York Charlotte Chicago Cleveland Dallas **Des Moines** Denver Houston Indianapolis Honolulu Las Vegas Los Angeles Miami Minneapolis New Orleans New York Oklahoma City Omaha Philadelphia Phoenix Portland Oregon Rio Arriba, New Mexico Sacramento Salt Lake City San Antonio San Diego San Jose Seattle Spokane Tampa Tucson Tulsa Washington D.C. Woodbury County Iowa

Variable	VIF	
Relative Neighborhood Disadvantage	1.06	
Homeless	1.04	
Minority Status:		
Black	1.48	
Hispanic	1.26	
Other Minority	1.12	
Educational Underachievement	1.10	
Employment Status:		
Unemployed	1.12	
Other Employment	1.09	
Offense Severity:		
Misdemeanor	1.20	
Traffic/Local Ordinance	1.23	
Offense Charge:		
Drug	1.80	
Property	1.70	
Other Offense	2.12	
Never Been Arrested	1.78	
Never Been to Jail	1.82	
Age	2.16	
Marital Status:		
Single	1.71	
Divorced/Separated/Widowed	1.59	
Hours Since Arrest	1.04	
Previous Outpatient Treatment	1.07	
Interviewer Age:		
Older Than Respondent	1.54	
Younger Than Respondent	2.04	
Female Interviewer	1.01	
Different Race Than Respondent	1.14	
Quarter:		
Second	1.42	
Third	1.43	
Fourth	1.25	

Appendix B

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