Does Employee Substance Abuse Predict Fraud?

ABSTRACT

Motivated by survey evidence, we examine the relation between worker substance abuse and workplace fraud. In our sample of white-collar professionals, nearly 10% of all frauds occur in the 0.01% of worker-years where the worker receives a professional sanction for substance abuse. Workers receiving such a sanction are between 40 and 50 times more likely to commit fraud in the current year relative to their peers. These results are consistent with prior research suggesting that substance abuse creates financial pressures and impairs neural functioning of self-regulatory mechanisms, both of which make fraud more appealing. We also find that there is no increased likelihood to commit fraud among workers with past or future substance abuse sanctions. This suggests that (1) workers with past but not current substance problems are not a fraud risk, and (2) the results we observe are driven by actual substance abuse, as opposed to stable personality traits predictive of both fraud and substance abuse. This study has implications for employers and policymakers as they consider both how to prevent fraud and how to reduce the negative impact of substance abuse in the workplace through internal control systems and practices like Employee Assistance Programs.

Keywords: Substance abuse, fraud, behavioral finance, impulsivity, delay discounting

JEL Codes: K42, G02, M12, M41, M51

Data Availability: The National Practitioner Data Bank public research file used in this paper is freely available for public download at https://www.npdb.hrsa.gov/resources/publicData.jsp.

I. INTRODUCTION

"[…] my sense of it is that 95 percent of the [workplace related] larcenies I prosecuted were generated by cocaine addiction […] cocaine was the drug that got people into embezzlement."

Lawrence Tytla
Assistant State's Attorney
Connecticut Division of Criminal Justice
(Benedict 2005)

Fraud costs companies and their investors $1 trillion annually in the United States, according to a survey by the Association of Certified Fraud Examiners (2016). Given these large losses, practitioners and academics have long sought to understand the factors that cause and prevent fraud (Seidman 1939). Despite the large literatures on fraud in both accounting and finance (e.g., Farber 2005; Dechow et al. 2011; Karpoff et al. 2008), most of the work on the potential causes of fraud focuses on employees' individual traits, like narcissism, and environmental attributes, like the structure of equity incentives (e.g., Feng et al. 2011; Armstrong Larcker, Ormazabal, and Taylor 2013; Denis et al. 2006; Harris and Bromiley 2007; Kim et al. 2011). Building on theories in psychology and neuroeconomics, we extend the fraud literature by examining a *behavioral* predictor of fraud, employee substance abuse. Specifically, we contribute to the literature on fraud by addressing the following two research questions. Do employees' substance abuse[1] habits relate to their likelihood of committing fraud in the workplace? Can the risk of fraud from employee substance abuse be mitigated by sobriety, given substance abuse is a behavior not a personality trait (e.g. Schuerger, Tait, and Tavernelli 1982)?

Self-reported survey evidence indicates that substance abuse among employees is associated with fraud in the workplace. For example, a survey from the Association of Certified Fraud Examiners reports that 10 percent of financial reporting frauds involve employees with addiction problems, and the median loss for a fraud of any type involving employees with

[1] We define substance abuse as the habitual use of any drugs or alcohol to excess.

addiction problems is $225,000 (ACFE 2008). Further, substance abuse is not just associated with fraud among low-level employees. Approximately 10 percent of full-time, white-collar professionals in management or finance roles struggle with substance abuse disorders (Bush and Lipari 2015), and that ratio increases to about 25 percent among former Wall Street workers (Tuttle 2013). Relatedly, survey evidence highlights that addiction problems among employees who commit workplace fraud are present in similar frequencies across ranks. Ten percent of lower-level employees, 10 percent of managers, and 8 percent of owners/executives who commit workplace fraud have addiction problems (ACFE 2016).

Motivated by these positive correlations in self-reported surveys, we hypothesize that, *ceteris paribus*, an employee with a substance abuse habit presents a higher fraud risk than one without. We expect this relationship for two reasons related to the incentive and rationalization elements of the fraud triangle. First, substance users have an economic incentive to steal or commit other illegal acts in order to financially support their substance habit (Inciardi 1981; Kinlock et al. 2003). Second, in addition to this economic motivation, results from neuroscience and psychology show that substance abuse causes poor impulse control and greater delay discounting (Jentsch and Taylor 1999; Kirby et al. 1999; Li et al. 2007; Madden et al. 1997; Petry 2001; Hamilton and Potenza 2012; Moeller and Dougherty 2002). Greater delay discounting translates to substance abusers being more likely to believe a small, immediate payoff is in their best interest as opposed to a larger, delayed payoff. For example, Madden et. al. (1997) observe that, when given a choice between immediate or future payouts, the implied annual discount rate for heroin addicts is about eight times higher than for matched control participants. Given this high value on immediacy, substance abusers may have an easier time justifying a fraud that pays out immediately, even if that means jeopardizing a valuable future cash flow stream like a salary.

To test the relationship between substance abuse and fraud in the workplace, we use data on medical doctors' professional sanctions. State medical boards make these data publically available in the National Practitioner Data Bank maintained by the U.S. Department of Health and Human Services.

The data report medical doctors' malpractice lawsuit settlement history and sanctions by state regulatory boards for violations of professional standards. The state regulatory board violations encompass a myriad of activities from abusing patients to allowing an unlicensed person to practice medicine. Notably for our study, the violations also include substance abuse violations like narcotics violations and alcohol abuse, as well as fraud-related violations like asset misappropriation, tax fraud, and insurance fraud. We construct a 10-year panel with these data, and, after adjusting for some selection issues, we estimate a series of logit regressions that examine whether employees' substance abuse habits are associated with the likelihood of their committing workplace fraud.

Consistent with our prediction, we find a positive association between employee substance abuse habits and their propensity to commit fraud. Among physicians receiving professional sanctions for substance abuse in year *t*, their likelihood of committing fraud in year *t* is higher than peers' by a factor of about 40. This increase in fraud likelihood remains after controlling for other possible predictors of fraud like a prior history of fraud inferred through prior fraud sanctions, a disregard for rules inferred through prior sanctions of unprofessionalism, and incompetence inferred through the number of prior malpractice lawsuits. Since the base rate of fraud is quite low in the NPDB sample, we also confirm that our results hold in a series of rare event logit models (Tomz et al. 2003).[3]

We then examine whether discontinuation of substance abuse mitigates the likelihood to commit fraud or whether the likelihood of fraud remains higher for recovered, sober employees than for employees who never abused substances. We find that the positive relation between substance abuse in year *t* and the propensity to commit fraud in year *t* is completely mitigated by time. That is, we observe no relation between substance abuse sanctions in year *t-1* (or before) and fraud in year *t*. This finding is consistent with neuroscience research showing that the brain can repair some of the damage inflicted upon its prefrontal cortex by substance abuse (e.g. Reneman et al. 2001). This result is also consistent with a reduced monetary incentive to commit fraud once employees no longer need to pay for a substance habit.

This paper makes three contributions to literatures in accounting and finance as well as psychology and neuroscience. First, we contribute to the literatures in accounting and finance that investigate the determinants of fraud (e.g., Call et al. 2016; Dechow et al. 2011). We provide empirical evidence that an employee's substance abuse habit is predictive of fraud in the workplace. Prior research examining this link between substance abuse and fraud are mostly surveys and interviews in practitioner reports (i.e., ACFE 2008, 2016). This study is the first to directly test the relation using naturally occurring data (i.e., the data on the professional sanctions of doctors by state medical boards). Additionally, we use panel data to isolate the effect of the substance abuse *behavior* independent of other employee traits like narcissism and Machiavellianism. We provide an estimate of how much the behavior of substance abuse

[3] The low fraud frequency in our physician sample (i.e., 220 fraud cases out of about 700,000 doctor-years) is similar to the low fraud frequency in existing accounting and finance literatures. For example, Dechow et al. (2011) only finds 494 firm-years with Accounting and Auditing Enforcement Releases (reports issued by the SEC after investigations against companies for alleged accounting or auditing misconduct) out of 132,967 firm-years.

increases the likelihood that employees commit fraud, and we show that this increased likelihood can be mitigated if the employees are able to recover their sobriety (proxied by a period free from substance abuse sanctions). Second, we contribute to the stream of accounting research that connects the foundation of accounting to the biological underpinnings of the human brain (e.g. Waymire 2014; Dickhaut, Basu, McCabe, and Waymire 2010). Although we do not directly test the brain function, our results are consistent with the theory that substance abuse could impair neural functioning of self-regulation and increase the likelihood of fraud. Lastly, our findings extend the literature in psychology and neuroscience by providing corroborating evidence of impaired impulse control and delay discounting stemming from substance abuse in a practical setting outside the laboratory.

Our study has implications for employers and policymakers alike. Our results demonstrate the potential benefit to employers of screening prospective employees for substance abuse during the hiring process through procedures like questionnaires, background checks, and drug tests (French, Roebuck, and Alexandre 2004). Additionally, the results show the importance of monitoring the existing workforce for signs of substance abuse and incorporating those signs into both company fraud risk assessments and responses to fraud risk. Perhaps more importantly, our findings emphasize the importance of good internal controls in the workplace.[4] A substance abuse habit greatly increases the likelihood of an employee committing fraud in the workplace, which suggests that it may be efficient to deploy scarce internal control resources (which can mitigate the likelihood and risks of workplace fraud) towards monitoring individuals or groups of employees with suspected substance abuse habits. Furthermore, we contribute to the

[4] We broadly define internal control as measures and processes in place to assure operational effectiveness and efficiency in an organization. According to this definition, the drug-driven fraud risk in this paper fall into an organization's risk management process, therefore, part of the internal control process.

literature that documents the advantages to employers of providing employee-friendly policies and high-quality benefits (e.g., Guo, Huang, Zhang, and Zhou 2015). Our results imply that abstinent substance abusers display no incremental fraud risk relative to workers with a history of substance abuse sanctions. This finding indicates that Employee Assistance Programs, employer-sponsored interventions that shepherd employees through addiction, family issues, and other emotional crises, could be an important element of a company's internal control system.[5]

This paper is organized as follows. Section II develops the background, theory, and hypotheses. Sections III and IV discuss the methodology and the results, and Section V concludes.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Predictors of Workplace Fraud

Workplace fraud encompasses misappropriation of assets, corruption, and financial statement fraud. Misappropriation of assets includes schemes from falsifying expense reimbursements to stealing inventory. Bid rigging and bribery are examples of corruption frauds. Financial statement frauds hardly need an introduction with the major headlines that accompany their exposure, but they include overstating revenue by including fictitious revenues and understating expenses by improperly capitalizing expenditures. In the United States alone, workplace fraud is estimated to cost businesses and investors about $1 trillion *per year* (ACFE 2008, 2016).

[5] Employee Assistance Programs are work-life and wellness services provided to employees by the employer and often include programs that focus on providing counseling and treatment for employees troubled with substance abuse issues and other personal problems (see Scanlon 1991; Attridge 2015; and Hartwell et al. 1996). These programs are provided by over 80 percent of medium and large employers in the United States (Attridge 2015).

Given the high costs of fraud, practitioners, policymakers, and researchers in accounting and finance have long been interested in the occurrences, predictors, and consequences of workplace fraud. Unsurprisingly, this interest has led to a broad literature on the topic (e.g., Dechow et al. 2011; Karpoff et al. 2008). For example, documented predictors of fraud include high-powered incentives (Feng et al. 2011; Armstrong et al. 2013; Denis et al. 2006; Harris and Bromiley 2007; Kim et al. 2011; Call, Kedia, and Rajgopal 2016), conflicts of interest (Dimmock and Gercken 2012), and weak boards of directors (e.g., Beasley 1996; Klein 2002). Most of these findings are consistent with intuition, in that fraud is more likely when firm profits map more directly to higher compensation and when oversight is lax (see also, Lennox and Pittman 2010).

Research in finance and accounting has also documented associations between individual characteristics and fraud. Some characteristics that correlate with fraud include age, education, work history, and certain personality traits (see Zahra, Priem, and Rasheed 2005 for a review). Military experience, for example, is associated with a lower likelihood of committing fraud (Benmelech and Frydman 2014), as is religious adherence (Callen and Fang 2015). High testosterone, meanwhile, is associated with a higher likelihood of committing fraud among managers (Jia, Van Lent, and Zeng 2014). This testosterone finding is consistent with the survey evidence indicating that males are more likely than females to commit white-collar crime (Blickle, Schlegel, Fassbender, and Klein 2006). This same survey finds that other individual characteristics correlate with fraud as well, including low self-control, high narcissism, and high hedonism (Blickle et al. 2006). Similarly, Accounting and Auditing Enforcement Release evidence shows that CEOs higher in narcissism are more likely to commit fraud than those lower in narcissism (Rijsenbilt and Commandeur 2013). Related findings also tie CEO overconfidence to increased misreporting and fraud (Schrand and Zechman 2012; Banerjee, Humphery-Jenner, Nanda, and Tham 2015; Ahmed and Duellman 2013).

These studies are just a few of the many that demonstrate that individual characteristics are useful predictors of fraud. Individual characteristics and environmental factors, like corporate governance structure or company culture (Biegelman and Bartow 2012), are not, however, the only useful predictors of fraud. For example, a budding literature on vocal cues ties managers' use of evasive language to fraud (Hobson, Mayew, and Venkatachalam 2011; Larcker and Zakolyukina 2012). We extend this fraud literature by focusing on another *behavior*, exclusive of traits and environmental factors, as a predictor of fraud and accordingly investigate whether this behavior (substance abuse) is predictive of workplace fraud.

Substance Abuse and Workplace Performance

Despite the dearth of research on the possible connection between substance abuse and workplace fraud, studies do exist on the relationship between substance abuse and other workplace outcomes, like absenteeism and involuntary turnover.[6] For example, U.S. Postal Service workers who tested positive for illicit drugs during their pre-employment screenings had a 59.3 percent higher absence rate than their peers who tested negative for illicit drugs (Normand, Salyards, and Mahoney 1990). Additionally, workers who tested positive were 1.55 times more likely to be fired than those who tested negative (Normand et al. 1990). This relation between substance abuse and exiting the workforce is consistent with an analysis of the 1997 National Household Survey on Drug Abuse, which shows that chronic drug use is associated with a higher likelihood of unemployment (French, Roebuck, and Alexandre 2001) as well as a

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[6] For an excellent literature review of the workplace implications of employee alcohol and drug use, see Harris and Heft (1992).

survey of military applicants that reveals a positive correlation between the extent and duration of drug use and unsuitability for employment (McDaniel 1988).

Substance abuse is also associated with a variety of negative personal outcomes for the abuser. These outcomes include poor health (Fox, Merrill, Chang, and Califano 1995), dropping out of school, and criminal behavior (United Nations Secretariat 1983). Given the association of substance abuse with those negative outcomes, intuition tempts us to label substance abusers as merely another group of "bad actors" who are unbothered by breaking rules and hurting others. Substance abuse, however, is not a stable personality trait (like Machiavellianism or sociopathy, for example). Individuals who abuse drugs may not always abuse drugs. The drug abuse is a *behavior*, not a personality trait. Although managers can benefit from identifying personality traits linked to fraud among their employees, they can also benefit from identifying *behaviors* linked to fraud. Unlike personality traits, behavior can be altered. If substance abuse predicts fraud, then managers can implement procedures to screen out prospective employees who abuse drugs and can invest in programs to eliminate this behavior among existing employees, thereby lowering fraud risk.

Substance Abuse and The Fraud Triangle

Statement on Auditing Standards No. 99 (SAS 99) highlights the fraud triangle, which shows three conditions that tend to be present when fraud occurs (i.e., AICPA 2002; Hogan, Rezaee, Riley, and Velury 2008). The first condition is that there is an incentive or motivation to commit fraud. The second is that there is an opportunity to commit fraud, and the third is that there is a rationalization to commit fraud (AICPA 2002). We expect substance abuse will increase the likelihood of fraud via both the incentive/motivation and rationalization corners of the triangle, as substance abuse is both expensive to maintain and reduces impulse control. The higher expenses increase the abuser's motivation and incentive to commit fraud, and the reduced impulse control could lessen the need for the substance abuser to rationalize the fraud before committing it.

Monetary Demands of Substance Abuse

Related to the incentive corner of the triangle, drug habits are expensive and often cause addicts to turn to crime in order to fund their drug abuse. The typical heroin addict, who uses 21+ days in a given month, spends about $1,800 per month on heroin. Chronic users of methamphetamine and cocaine tend to use less frequently (4-10 days per month) but still spend around $800 on a monthly basis to support their drug use (Kilmer et al. 2014). Although the crime derived from these drug expenses is difficult to measure, survey evidence allows for a rough approximation of their magnitude. Inciardi (1981), for example, observes that the typical narcotics addict in his sample (n=543) is responsible for, in a one year period, 11 robberies, 12 burglaries, 1.6 stolen cars, 46 instances of shoplifting, and 85 incidences of larceny. Surveys of white-collar heroin addicts are not dissimilar. Faupel (1988), for example, notes that these workers commit an average of 94 property crimes per year (theft, burglary, shoplifting, pickpocketing, forgery, fraud, and larceny).

This economic incentive undoubtedly creates some pressure to commit fraud among white-collar substance users, but we believe reduced rationalization also contributes to the frequency and severity of their committed frauds. Not only is there compelling evidence for this mechanism in neuroscience and psychology research, but the salary of a typical physician, even in the most modestly compensated specialties, is likely high enough to sustain even a full blown heroin or cocaine habit.[7] While an $1,800 per month drug expense is not cheap, in constant

[7] Daily cocaine users spend an average of $1,737 per month on their habit (Kilmer et al. 2014).

(2010) dollars, such a figure only makes up about 14 percent of the monthly income of a primary care physician (Guglielmo 2011).[8]

Impeded Impulse Control and Substance Abuse

In addition to these economic pressures, substance abuse likely makes it easier for a potential fraudster to rationalize his or her actions.[9] In neurological studies based on MRIs, repeated substance abuse has been shown to interfere with the neural pathways that control and inhibit impulsivity (Koob and Bloom 1988; Koob and Volkow 2016). Accordingly, we expect substance abusers to be less likely to permit ethical concerns or self-image maintenance to overwhelm the impulse to commit fraud (Jentsch and Taylor 1999; Li et al. 2011). Furthermore, substance addicts have been shown to have higher discount rates than matched peers, which suggests that substance users may be more willing to risk the long-run payoff tied to a well-paying medical position for an immediate, fraudulent payoff. For example, heroin addicts preferred an immediate reward of lower value over a time-delayed reward of greater value more than non-addicts of similar age, gender, education, and IQ (Madden, Petry, Badger, and Bickel 1997; Kirby, Petry, and Bickel 1999). After a one-year delay, heroin addicts discounted the value of $1,000 by 60 percent, whereas non-addicts still had not discounted $1,000 by 60 percent after *five* years (Madden et al. 1997).[10] This steep pattern of discounting in heroin addicts represents a

[8] Furthermore, physicians with a substance dependence problem are much more likely to suffer from alcoholism than an addiction to a more expensive substance like cocaine or heroin. Oreskovich et al. (2015) find that about 15 percent of U.S. physicians struggle with alcohol abuse or dependency.

[9] For thorough discussions of rationalization, see Murphy and Dacin (2011) and Festinger (1957, 1962).

[10] Similar results have been found in substance users dependent on cocaine (e.g., Heil, Johnson, Higgins, and Bickel 2006; Coffey, Gudleski, Saladin, and Brady 2003; Mendez et al. 2010), marijuana (e.g., McDonald, Schleifer, Richards, and de Wit 2003), amphetamines (e.g., Hoffman et al. 2008), alcohol, and tobacco (Petry 2001; Bickel, Odum, and Madden 1999).

poorer ability to control impulsiveness than that found in sixth grade children (Madden et al. 1997; Green, Fry, and Myerson 1994).[11]

All told, higher impulsivity and steeper delay discounting likely lower the hurdle for rationalization faced by substance abusers considering fraud. Clearing this rationalization hurdle is further eased in substance abusers by a steep delay discount, which encourages them to look more favorably on risking the long-run payoffs associated with secure employment in exchange for the smaller but immediate returns to a fraud.

Hypothesis Development

The literature reviewed above highlights that, relative to their peers, substance abusers have stronger incentives to commit fraud and an easier time rationalizing the decision to commit fraud. We use these twin mechanisms to motivate our hypothesis below, stated in the alternate form.

> ***Hypothesis****: A substance abuse habit is positively associated with the likelihood of a white-collar professional committing fraud in the workplace.*

Despite the evidence documented above, we note that this hypothesis is not without tension. Comer (1994) provides an overview of the drug testing and performance literature, and she notes that while some studies document that substance abusers are more likely to get fired and miss work (e.g., Normand et al. 1990, Zwerling et al. 1990), research on the actual performance of substance users is mixed. For example, Parish (1989) finds no difference in performance evaluation or retention between users and nonusers, and Lehman and Simpson (1992) observe only that users are more likely to exhibit withdrawal symptoms at work (but no

[11] Neurologically, this impaired inhibitory control stemming from substance addiction is thought to originate from the damaging effect of substance abuse on the frontal cortex, which is the part of the brain responsible for estimating consequences and distinguishing good actions from bad (Jentsch and Taylor 1999; Li et al. 2007).

differences in workplace performance). A small literature does observe suitability and performance problems in samples of substance users (e.g., McDaniel 1988, Mangione et al. 1999), but overall this is not a decided question. Additionally, we examine a population of employees who work in a profession with an ethical code and related standards. It is possible that professional ethics provide a countervailing force against workplace fraud regardless of substance abuse (e.g., Smith 2016, Schwartz 2001, Parker 1994).

III. DATA AND METHODS

The data in this study are drawn from the National Practitioner Data Bank (NPDB) public research file. This data set tracks negative events in the careers of healthcare professionals with a goal of identifying dangerous practitioners. The data are maintained by staff within the Bureau of Health Workforce, a unit of the U.S. Department of Health and Human Services. The data set consists of two distinct types of records, (1) malpractice payouts and (2) sanctions from insurers or state licensing boards. State medical boards collect these data and report them to the NPDB. Each record contains information on the specific event (e.g., a particular malpractice payout, state board sanction, or insurer sanction), physician in question (identified only by an ID number and decade of medical school graduation), year, and state. For example, if a doctor is convicted of a DUI, they are required to report this charge (and all misdemeanor and felony convictions/pleas) to the state medical board. Similarly, employers (hospitals, practices, etc.) are required to report doctors’ failed drug tests (among other incidences like fraud, unprofessionalism, sexual harassment, etc.) to the state medical board, which typically results in the board issuing a sanction of some sort to the doctor in question. These sanctions are typically accompanied by fines, counseling, probation, and/or a censure letter. Records of these sanctions are made available by state medical boards to the NPDB, and ultimately the public in anonymized format (via the NPDB public research file).

One challenge with this data set is that it only includes doctors who have settled malpractice lawsuits (or had an insurance company settle on their behalf) or who have received a sanction from their state board. It therefore excludes doctors without sanctions or malpractice settlements. This exclusion is problematic if the data set only leaves us with physicians who are bad actors. The generalizability of our study would be limited if we could only speak to the relation between fraud and substance abuse in a sample of bad actors. To address this concern, we only include physicians with malpractice settlements in our panel instead of using the entire data set. This design choice stems from research in medicine and public health that finds little relation between physician quality and malpractice lawsuit likelihood (Kocher et al. 2008). If anything, physicians holding board certifications and degrees from prestigious medical schools are more likely to be subject to malpractice lawsuits, perhaps because these physicians are more likely to be specialists who take on high risk patients (Sloan, Mergenhagen, Burfield, Bovbjerg, and Hassan 1989). This literature suggests that by selecting only the doctors in the malpractice sample and using that sample to examine the relationship between substance abuse and fraud, we can identify the effect of substance abuse on workplace fraud in a quasi-random sample, as opposed to a sample selecting observations for inclusion based on misconduct, low skill, or other "bad actor" traits.

The malpractice sample overlaps with the sanctions sample to some degree, and, by focusing on malpractice defendants, we hope to remove much of the bias from our sample selection procedure. Malpractice lawsuits, unlike professional sanctions, are largely a function of specialty and not misconduct. By age 65, for example, 99 percent of doctors in high risk specialties report being the subject of at least one malpractice lawsuit during their career.[12] On an annual basis, about 8 percent of physicians in high risk specialties are involved in malpractice suits with a payout, and about 2 percent of physicians in low risk specialties are successfully sued for malpractice (Jena, Seabury, Lakdawalla, and Chandra 2011).

After selecting those physicians in NPDB who were subject to malpractice settlements, we build a panel running from 2000 to 2009 for all those physicians who graduated from medical school in the 1980s and 1990s. We make this design choice for several reasons. First, many of the cross-sectional variables of interest on sanctions, including several proxies for substance abuse, have only been recorded since the mid-1990s. Starting the sample in year 2000 ensures us that at least a few years of these data have been collected, which better enables us to identify doctors with substance abuse issues during the entire time period of our sample. Second, focusing our tests on doctors who graduated in the 1980s and 1990s ensures us that every doctor in our sample likely remains in our sample from beginning to end. Even doctors who graduated from medical school in 1980 are likely still practicing in 2009. Including earlier cohorts of medical school graduates, or examining more recent years of data, would weaken this assumption. All told, about 70,000 unique doctors enter our sample. American medical schools produced about 16,000 graduates per year during the 1980s and 1990s (AAMC 2012), suggesting that about 20 percent of the potential underlying population of practicing physicians enters our sample.

We use the sanctions reported by state medical boards to the NPDB to construct our primary variables of interest. These sanctions stem from complaints received by the boards from colleagues and patients, state board investigations, and reports from medical firms like hospitals,

[12] About 30 percent of medical malpractice lawsuits involve a payout at conclusion, and many suits are dismissed.

large practices, and insurance companies. The NPDB records many types of misconduct (see Appendix A for the subset we include in our analysis), and we focus on fraud as our dependent variable. Table 1 reports the frequencies of the different fraud sanctions in our sample. The most common sanctions are for unspecified fraud, falsifying records, and credentialing fraud (i.e., claiming unearned credentials in order to qualify for higher insurance reimbursements). Unsurprisingly, among our sample of well-paid professionals, the base rate of these workplace frauds is low (220 fraud cases, or about 0.03% of all doctor-year observations).

NPDB substance abuse misconduct records involve cases of driving under the influence, stealing narcotics from workplace supplies, failing workplace drug tests, and coming to work under the influence. Table 2 reports the breakdown of substance abuse sanctions by frequency and cohort of medical school graduation (by decade). For example, 22,419 physicians who graduated from medical school in the 1990s enter our sample. Of these, by the end of our sample period, 119 were sanctioned once for substance abuse violations, 41 were sanctioned twice, five were sanctioned three times, one was sanctioned four times, and one physician was sanctioned five times. All told, in our sample of 70,801 physicians, less than 1 percent of them (662 total) are sanctioned at least once for substance abuse infractions prior to or during our sample period (Table 2).

Next, we attempt to model whether or not these doctors with substance abuse problems are responsible for a disproportionate amount of fraud. To do so, we estimate models predicting fraud sanctions as a function of substance abuse sanctions in logistic regressions of the following type:

$$\textit{Prob}\ (\textit{Fraud}_t) = f\ (\textit{Substance Abuse Sanction, Controls}) \qquad (1)$$

where the dependent variable equals one if the doctor committed workplace fraud, and zero otherwise. Our variable of interest on the right-hand-side of equation (1), *Substance Abuse Sanction*, equals one if the doctor has been sanctioned for a substance abuse issue, and zero otherwise. We split this variable of interest into seven different test variables for our regression models based on the time of the sanctions. We do this because we are interested in discovering the timing when substance abuse behavior is predictive of fraud, in addition to establishing the association between the two variables. That is, are past (near or distant) substance abuse behaviors predictive of fraud, or is the effect concentrated among those with current substance abuse problems? For completeness, and to further rule out the alternative explanation that our results are driven by stable personality traits, we also include variables that load in the case of a doctor who will see a professional sanction for substance abuse in the future. We label these variables such that the time-variant subscript indicates the year of substance abuse sanction, relative to the focal year: *Substance Abuse Sanction*$_{t\text{-}3\ or\ more}$, *Substance Abuse Sanction*$_{t\text{-}2}$, *Substance Abuse Sanction*$_{t\text{-}1}$, *Substance Abuse Sanction*$_{t}$, *Substance Abuse Sanction*$_{t+1}$, *Substance Abuse Sanction*$_{t+2}$, and *Substance Abuse Sanction*$_{t+3\ or\ more}$.

We control for other sanctions related to personality traits that may be correlated with substance abuse and fraud, such as a general indifference towards good behavior and other-regarding concerns (as in Majors 2016). Specifically, we include dummy variables for past professional sanctions to control for unprofessionalism (*Unprofessionalism Sanction*), criminal convictions (*Criminal Sanction*), sexual harassment (*Sex Offense Sanction*), and negligence (*Malpractice Sanction*).[13] To account for the severity of such sanctions, we also include indicator variables denoting whether or not a state specific medical license has ever been revoked (or

[13] Due to data limitation, we do not have variables directly measuring personality traits. We, thus, control for variables that may be highly correlated with personality traits.

reinstated) for the physicians in our sample (i.e., *License Suspension* and *License Reinstatement*). We also control for past sanctions for fraud (*Fraud Sanction*$_{t\text{-}1\ or\ more}$), as a variety of research has shown past fraud to be a powerful predictor of contemporaneous fraud (Porcano 1988; Dimmock and Gerken 2012; Shu and Gino 2012; Ruedy, Moore, Gino, and Schweitzer 2013; Rajgopal and White 2016).

In addition, we include a count and cumulative sum of medical malpractice payouts as control variables for each doctor-year in our sample. Many doctors are sued for malpractice at least once in their careers, but poorly trained doctors are sued more often (Adamson, Baldwin, Sheehan, and Oppenberg 1997). By including these malpractice payouts in our models, we can, at least partially, control for skill and associated earning potential. This is important, given that low income has also been identified as a fraud predictor in some studies (Slemrod, Blumenthal, and Christian 2001; Christian 1994; Orviska and Hudson 2003).

The summary statistics for these control variables, as well as our variables of interest, are reported in Table 3. We use these panel data to estimate logistic regressions predicting the likelihood of each doctor in our sample committing fraud in a given year, with a primary interest in whether this rate is increasing for doctors with substance abuse problems (and associated sanctions). All of these logit models include standard errors clustered at the doctor level.

IV. RESULTS

Fraud and Past Substance Abuse Results

Table 4 reports the results of our primary set of logit models. Models 1 through 7 include the time-variant versions of *Substance Abuse Sanction* one by one, and model 8 includes all of these versions of *Substance Abuse Sanction* in a single specification. We report odds ratios in Table 4 for better interpretation of economic significance.

The most striking result in this table is the effect of contemporaneous substance abuse sanctions on contemporaneous fraud (*Substance Abuse Sanction*$_t$). The coefficients for *Substance Abuse Sanction*$_{t-1}$, *Substance Abuse Sanction*$_t$, *Substance Abuse Sanction*$_{t+1}$ are positive and significant in models 3 to 5, respectively. However, only *Substance Abuse Sanction*$_t$ remains statistically significant in model 8, where we include all the time-variant versions of *Substance Abuse Sanction*. Results in model 4 and model 8 indicate that substance abuse sanction is predictive of contemporaneous fraud.

Turning to the economic significance of *Substance Abuse Sanction*$_t$, the odds ratios in models 4 and 8 are around 40. These results suggest that in our sample of physicians, those currently struggling with substance abuse are about *40 times* more likely to commit fraud than their peers without contemporaneous substance abuse sanctions. In model 4, for example, the likelihood of a median physician (all controls set to median) committing fraud in a given year is 0.02%. Shifting *Substance Abuse Sanction*$_t$ from 0 to 1 for this otherwise median physician increases the predicted likelihood of fraud to 0.88%. Although fraud rate may appear low on an absolute scale, it represents a substantial increase in the propensity of fraud relative to baseline levels. We, therefore, interpret that the economic significance of *Substance Abuse Sanction*$_t$ is considerable.

Beyond this test variable, there does not appear to be a convincing relation between current year fraud and substance abuse in other years (*t-3 or more, t-2, t-1, t+1, t+2,* and *t+3 or more*). Models 3 and 5 find significant odds ratios on *Substance Abuse Sanction*$_{t-1}$ and *Substance Abuse Sanction*$_{t+1}$, respectively, but those findings do not persist in model 8 (which also includes

Substance Abuse Sanction$_t$). Broadly, these findings indicate that, excluding doctors with current year substance abuse problems, doctors with substance problems in the past (and future) present no increased risk of fraud to their employers or customers. This also provides an argument against our findings relating to *Substance Abuse Sanction$_t$* being driven by stable personality traits that could drive both substance abuse and fraud (Majors 2016; LaViers 2017). If the results were driven by personality traits, we would observe the correlation between substance abuse sanction and fraud holds across all specified times, as personality traits do not change. Rather, the relation we identify is not driven by fraudsters who happen to be the type of person that falls into substance abuse. Those individuals are not more or less likely to commit fraud in our sample, *except* for those years when there is evidence to suggest that they have an active and ongoing substance abuse problem (that is, when *Substance Abuse Sanction$_t$*=1). For policy-makers and employers, this also suggests that background checks that screen for substance abuse problems (drug related arrests, DUIs, etc.) may not be as effective in preventing fraud as checking for current substance problems in the workforce, perhaps via periodic drug tests or observation.

Beyond our variables of interest related to substance abuse, these results confirm, in line with prior research, that past fraud sanctions are powerful predictors of current fraud (e.g., Porcano 1988; Dimmock and Gerken 2012; Shu and Gino 2012; Ruedy et al. 2013; Rajgopal and White 2016). Other predictors of workplace fraud include the count of past malpractice lawsuits settled (perhaps indicative of lower skill) and past license suspensions by the state medical board (likely a function of prior severe misconduct).

To engender a better understanding of our unusually distributed data set, in Table 5 we provide a 2x2 cross-tabulation of our dependent variable (*Fraud Sanction$_t$*) and most influential variable of interest (*Substance Abuse Sanction$_t$*). The fraud rate in the treated sample (where *Substance Abuse Sanction$_t$*=1) is 3.4%, whereas the fraud rate in the control sample (where *Substance Abuse Sanction$_t$*=0) is only 0.03%. In line with the logit models introduced previously, a Fisher's Exact Test (provided below the cross-tabulation) confirms that the fraud rate among doctors with a current year substance abuse sanction is significantly higher than that among their peers without such sanction ($p<0.001$).

However, a more interesting observation stemming from this table is the fact that nearly 10% of all fraud cases in our sample (21/220) occur in the 0.01% of years in which a doctor receives a sanction for substance abuse (621/708,010). That is, a considerable portion of all frauds emit from the tiny minority of doctor-years involving a substance abuse sanction.

Sensitivity Check: Rare Event Logit Analysis

As a robustness check on our primary analyses, we estimate a series of rare event logistic regression models. Typical logit tests can be biased away from the null in situations in which the dependent variable is a rare event (i.e., dependent variable differs from the mode in less than 5 percent of cases, according to King and Zeng 2001). To correct for this potential bias, Tomz et al. (2003) develop a logit model specifically for rare events. Since frauds occur in only 0.03% of our observations, we re-estimate our primary tests using the rare event logit model of Tomz et al. (2003). Results for these models are presented in Table 6. For ease of interpretation, the full battery of control variables is suppressed from this output (but included in the underlying regressions)

Briefly, we find that the direction and significance of our results are unaffected by our choice of model. *Substance Abuse Sanction$_t$* is the only variable of interest that loads consistently, and the economic significance of this test variable remains unaffected by the rare logit models (odds ratio in the 40-45 range in models 4 and 8 in Table 6). Overall, this suggests that our findings do not result from biased econometric specifications emitting from predicting occurrences in the far tail of the distribution of outcomes.

Sensitivity Check: Coarsened Exact Matched Sample Analysis

Beyond the rare occurrence of frauds in our sample (adjusted for the in the prior analysis), we are also concerned about the possibility that doctors with substance abuse problems are different from their peers on multiple other dimensions. To ensure that this is not driving our findings, we next employ a coarsened exact matched sample in Table 7 (Iacus, King, and Porro 2011; Blackwell, Iacus, King, and Porro 2009). To do so, we match treated sample (those doctor-years when the doctor in question has a past, current, or future substance abuse sanction) to control sample by year, graduation cohort, other prior sanctions (for fraud, unprofessionalism, crime, malpractice, license suspensions and reinstatements), and malpractice lawsuit outcomes (number of past lawsuits and sum of past monetary awards, coarsened to the nearest $10,000).

For example, in the model 2 using *Substance Abuse Sanction*$_{t-2}$ as the variable of interest, treatment observations (where *Substance Abuse Sanction*$_{t-2}$=1) are matched to control observations (where *Substance Abuse Sanction*$_{t-2}$=0) equal on all other observable covariates. These matched covariates include control variables and other substance abuse variables of interest, like *Substance Abuse Sanction*$_{t-1}$. This allows for an apples-to-apples comparison, where the only observable difference between treatment and control samples comes from the treatment variable. In our example, this treatment variable is *Substance Abuse Sanction*$_{t-2}$.

We construct a coarsened exact matched sample for each of the 7 models in Table 7. This results in seven separate samples (one for each treatment variable), which explains the differing samples sizes in the Table 7 models. For brevity we omit summary statistics and covariate balance tables for these seven samples, but the summary statistics do not diverge greatly from those reported in Table 3. In untabulated results, the covariate balance for each sample is well within the cutoffs for a successful match suggested by Rubin (2001) and Austin (2009). They specify the standardized differences in means less than 0.1, and covariance ratios between 0.5 and 2.

We estimate each of our primary logit models using the exact matched sample corresponding to the treatment variable employed, and we report these logistic regressions in Table 7. We again observe that the only substance abuse variable predictive of fraud is *Substance Abuse Sanction$_t$*, which loads with an odds ratio of 50. Such economic magnitude is similar to the 40-45 range estimated in other specifications using the entire sample, presented in Table 4. Relative to matched peers, the odds ratio suggests that doctors with current substance problems (and receiving contemporaneous sanctions for substance abuse) are about 50 times more likely to commit fraud ($p<0.001$).

V. CONCLUSION

Using data from the National Practitioner Data Bank on medical doctors' sanctions by state regulatory boards, we investigate the relationship between doctors' substance abuse and workplace fraud. We find that the 0.01% of doctors struggling with substance abuse problems leading to sanctions in a given year are responsible for almost 10% of workplace frauds. Logit models suggest that these doctors with substance abuse sanctions in year *t* are between 40 and 50 times more likely to commit fraud in year *t* than their peers. We observe no effects, however, for doctors with past year (or future year) substance abuse sanctions. That is, a doctor with a substance abuse sanction in year *t-2* is no more likely than an unsanctioned peer to commit fraud in year *t*. This observation suggests that (1) our results are driven by contemporaneous substance abuse behavior, as opposed to stable personality traits predictive of substance abuse and fraud, and (2) that employees with past but not current substance abuse problems are unlikely to pose an elevated fraud risk.

Our findings are subject to a few limitations. First, our dependent measure is a rare event. We have low base rates for fraud and a large sample size. Although we conduct multiple supplemental analyses to address these distribution issues, such as a series of rare event logit models and a coarsened exact matched sample approach, the distribution of the data is not ideal. Second, our measures for substance abuse and for the commission of fraud only include doctors who are caught abusing substances or caught committing fraud. Because of this data restriction, both our measure of substance abuse and our measure of fraud are likely understated, and they may not be understated by the same rate. We, however, believe that the understated fraud sample biases against our results.

Last, we do not have direct evidence on whether our results generalize to the commission of financial statement fraud, which is perhaps the type of fraud that most interests participants in developed market economies. However, given that our hypothesis rests on substance abuse lowering the rationalization hurdle and increasing the incentive for fraud, we see no reason as to why other types of fraud would not be similarly spurred by substance abuse. Additionally, employees who commit fraud often commit multiple types. In their global survey, the Association of Certified Fraud Examiners found that only 16% of financial reporting frauds did *not* overlap with another fraud scheme. The remaining 84% of financial statement fraud cases involved additional asset misappropriation or corruption frauds in addition to the financial statement fraud (ACFE 2016). So, although our fraud data more closely relate to misappropriation of assets and corruption rather than financial statement fraud, we believe our findings do generalize to all types of workplace fraud and can be useful to those trying to prevent or detect fraud.

This study contributes to several literatures. We contribute to the accounting and finance literatures on fraud by demonstrating that substance abuse is a behavioral predictor of fraud among employees and that the fraud red flag can be mitigated once the behavior is rectified. We also quantify a conservative estimate of the damage that employee substance abuse can do to companies by estimating the increase in the likelihood of fraud when this behavior is present. Additionally, we contribute to the literatures in psychology and neuroeconomics on human decision-making and impulsivity. Economists have long sought to understand why and how the need for immediate gratification affects human decision making (e.g., Smith 1759; McClure et al. 2004). The rationality, or lack thereof, of individual intertemporal choice continues to be examined (e.g., Becker and Murphy 1988; Bickel and Marsch 2001). Our results document another instance of myopic delay discounting and demonstrate its impact in important business settings.

Our findings are important for employers and policymakers as they continue to work to prevent and detect fraud within companies. Not only do we provide evidence that substance abuse is an important behavioral red flag for fraud, we show that the red flag is mitigated when employees achieve sobriety (proxied imperfectly by at least one year free from substance abuse sanctions). This finding implies that initiatives like Employee Assistance Programs, which are intended to help employees through personal crises like substance abuse, could be a useful tool for fraud prevention in an internal control system.

Preempting fraud through the identification of its behavioral precursors could greatly reduce fraud costs. Although individuals who have committed fraud in the past are likely to commit it again (Porcano 1988; Dimmock and Gerken 2012; Shu and Gino 2012; Ruedy et al. 2013; Rajgopal and White 2016), most employees who commit workplace fraud have never committed fraud before. Only about one in twenty fraud perpetrators has previous fraud convictions, and only about one in twelve has been previously fired for fraud-related offenses (ACFE 2016). Identifying personal and environmental characteristics that predict fraud is important, but identifying behavioral cues is also important. Unlike individual traits, which are difficult or impossible to change, behavior can change. Behavioral determinants of fraud can be mitigated through changes in that behavior. Future research can investigate how companies can prompt constructive behavioral changes among their employees for the benefit of both the company and the employee.

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APPENDIX A
NPDB Sanctions Mapped to Covariates and Variables of Interest

This appendix lists the types of sanctions that we collect for in our data set, and it shows how we code those sanction types into our test and control variables. Note that this data set originates from the National Practitioner Databank maintained by the Department of Health and Human Services that tracks sanctions of licensed physicians issued by state-specific boards of medicine.

Sanction Category	Basis for Action (NPDB Code)	NPDB Code Definition
Fraud	5	Fraud (Unspecified)
	6	Insurance Fraud (Medicare and Other Federal Gov. Program)
	7	Insurance Fraud (Medicaid or Other State Gov. Program)
	8	Insurance Fraud (Non-Government or Private Insurance)
	9	Fraud in Obtaining License or Credentials
	16	Misappropriation of Patient Property or Other Property
	21	Failure to Repay Overpayment
	36	Violation of Federal or State Tax Code
	55	Improper or Abusive Billing Practices
	56	Submitting False Claims
	57	Fraud, Kickbacks and Other Prohibited Activities
	60	Felony Conviction Related to Health Care Fraud
	64	Conviction Re: Fraud
	D3	Exploiting a Patient for Financial Gain
	E1	Insurance Fraud (Medicare, Medicaid or Other Insurance)
	E3	Filing False Reports or Falsifying Records
	E4	Fraud, Deceit or Material Omission in Obtaining License or Credentials
Substance Abuse	1	Alcohol and/or Other Substance Abuse
	F2	Unable to Practice safely by Reason of Alcohol or Other Substance Abuse
	3	Narcotics Violation
	35	Drug Screening Violation
	61	Felony Conviction Re: Controlled Substance Violation
	66	Conviction Re: Controlled Substances
	75	Violation of Drug-Free Workplace Act
	H1	Narcotics Violation or Other Violation of Drug Statutes
Sex Offense	D1	Sexual Misconduct
	D2	Non-Sexual Dual Relationship or Boundary Violation
Criminal	19	Criminal Conviction
	62	Program-Related Conviction
	63	Conviction Re: Patient Abuse or Neglect
	65	Conviction Re: Obstruction of an Investigation
	69	Criminal Conviction, Not Classified
	70	Violation of By-Laws, Protocols or Guidelines
Unprofessionalism	10	Unprofessional Conduct
Malpractice, Negligence, and Medical Mistakes	12	Malpractice
	13	Negligence
	14	Patient Abuse
	15	Patient Neglect
	17	Inadequate or Improper Infection Control Practices
	25	Practicing Without a License
	29	Practicing Beyond Scope of Practice
	30	Allowing Unlicensed Person to Practice
	32	Lack of Appropriately Qualified Professionals
	52	Incompetence, Malpractice, Negligence (Legacy Format Reports)
	53	Failure to Provide Med Resnble or Nec. Items/Services
	54	Furnishing Unnecessary or Substandard Items/Services

APPENDIX B
Variable Definitions

Fraud Sanction$_t$: The doctor is sanctioned for fraud in the current year. See Appendix A for a list of fraud sanctions and Table 1 for the frequencies of these sanctions in our data.

Substance Abuse Sanction$_{t\text{-}3\text{ or more}}$: The doctor received a professional sanction for substance abuse 3 or more years ago. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_{t\text{-}2}$: The doctor received a professional sanction for substance abuse 2 years ago. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_{t\text{-}1}$: The doctor received a professional sanction for substance abuse 1 year ago. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_t$: The doctor received a professional sanction for substance abuse in the current year. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_{t+1}$: The doctor will receive a professional sanction for substance abuse 1 year into the future. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_{t+2}$: The doctor will receive a professional sanction for substance abuse 2 years into the future. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Substance Abuse Sanction$_{t+3\text{ or more}}$: The doctor will receive a professional sanction for substance abuse 3 or more years into the future. See Appendix A for a list of the different types of substance abuse sanctions in the NPDB data.

Fraud Sanction$_{t\text{-}1\text{ or more}}$: The doctor has been sanctioned for fraud in any past year. See Appendix A for a list of these sanctions in the NPDB data.

Sex Offense Sanction$_{t\text{-}1\text{ or more}}$: The doctor has been sanctioned for a sexual offense in any past year. See Appendix A for a list of these sanctions in the NPDB data.

Unprofessionalism Sanction$_{t\text{-}1\text{ or more}}$: The doctor has been sanctioned for unprofessionalism in any past year. See Appendix A for a list of these sanctions in the NPDB data.

Criminal Sanction$_{t\text{-}1\text{ or more}}$: The doctor has been sanctioned for a criminal charge in any past year. See Appendix A for a list of these sanctions in the NPDB data.

Malpractice Sanction$_{t\text{-}1\text{ or more}}$: The doctor has been sanctioned for medical malpractice in any past year. See Appendix A for a list of these sanctions in the NPDB data.

 # Malpractice Lawsuits Settled: The count of medical malpractice lawsuits the doctor has settled in past years. Includes malpractice lawsuits settled on behalf of the doctor by an insurance company.

Cumulative Malpractice Settlement $: The cumulative dollar value of medical malpractice lawsuits the doctor has settled in past years. Includes malpractice lawsuits settled on behalf of the doctor by an insurance company.

License Suspension$_{t\text{-}1\ or\ more}$: The doctor has had a medical license suspended (permanently or temporarily) by a state medical board or other regulator.

License Reinstatement$_{t\text{-}1\ or\ more}$: The doctor has had a medical license suspended (permanently or temporarily) and then reinstated by a state medical board or other regulator.

Tenure in years: Number of years that have elapsed between year t and the earliest year in the decade of the doctor's medical school graduation decade (more granular data on graduation date is not provided in the NPDB data).

1990s Graduation Cohort: We use only the 1980s cohort and 1990s cohort of medical school graduates in this study. In our models, we include a dummy variable for 1990s cohort, with the 1980s cohort serving as the excluded category.

Table 1
Fraud Sanction Frequencies by National Practitioner Data Bank Basis Code

Basis for Action (NPDB Code)	NPDB Code Definition	Frequency
5	Fraud (Unspecified)	47
6	Insurance Fraud (Federal)	3
7	Insurance Fraud (State)	2
8	Insurance Fraud (Private)	1
9	Fraud in Obtaining License or Credentials	15
36	Violation of Federal or State Tax Code	3
55	Improper or Abusive Billing Practices	13
56	Submitting False Claims	2
81	Misrepresentation of Credentials	1
E1	Insurance Fraud (Medicare, Medicaid, or Other Insurance)	12
E3	Filing False Reports or Falsifying Records	34
E4	Fraud, Deceit or Material Omission in Obtaining License or Credentials	87

TABLE 2
Frequency Distribution of Substance Abuse Sanctions by Medical School Graduation Cohort

This table reports the distribution of physicians in our sample by decade of graduation and by number of substance abuse sanctions in the data set by the end of our sample period (2009). Physician (MD) demographics are only reported at the decade level, thus the breakdown by graduation decade rather than year. See Appendix A for the types of substance abuse sanctions captured in these data.

		Distribution of Substance Abuse Sanctions by MD at End of Sample Period (2009)							
		0	1	2	3	4	5	6	Total
Cohort	1980s	47,887	344	101	31	12	6	1	48,382
	1990s	22,252	119	41	5	1	1	0	22,419
		70,139	463	142	36	13	7	1	70,801

TABLE 3
Descriptive Statistics

This table reports the summary statistics (by doctor-year) of the dependent, test, and control variables for the 70,801 physicians in our panel over our ten-year sample period (2000-2009). The control variables are mostly collected from the NPDB data set. See Appendix A for the types of sanctions captured in these data.

Variable	Person-year obs.	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Fraud Sanction in Current Year	708,010	0.00031	0.01763	0	0	0	0	1
Substance Abuse Sanction$_{t\text{-}3 \text{ or more}}$	708,010	0.00552	0.07410	0	0	0	0	1
Substance Abuse Sanction$_{t\text{-}2}$	708,010	0.00087	0.02941	0	0	0	0	1
Substance Abuse Sanction$_{t\text{-}1}$	708,010	0.00089	0.02982	0	0	0	0	1
Substance Abuse Sanction$_{t}$	708,010	0.00088	0.02960	0	0	0	0	1
Substance Abuse Sanction$_{t+1}$	708,010	0.00087	0.02956	0	0	0	0	1
Substance Abuse Sanction$_{t+2}$	708,010	0.00087	0.02944	0	0	0	0	1
Substance Abuse Sanction$_{t+3 \text{ or more}}$	708,010	0.00527	0.07237	0	0	0	0	1
Fraud Sanction$_{t\text{-}1 \text{ or more}}$	708,010	0.00154	0.03924	0	0	0	0	1
Sex Offense Sanction$_{t\text{-}1 \text{ or more}}$	708,010	0.00057	0.02379	0	0	0	0	1
Unprofessionalism Sanction$_{t\text{-}1 \text{ or more}}$	708,010	0.01039	0.10142	0	0	0	0	1
Criminal Sanction$_{t\text{-}1 \text{ or more}}$	708,010	0.00181	0.04248	0	0	0	0	1
Malpractice Sanction$_{t\text{-}1 \text{ or more}}$	708,010	0.00799	0.08901	0	0	0	0	1
# Malpractice Lawsuits Settled	708,010	1.078	1.291	0	0	1	1	150
Cumulative Malpractice Settlement $	708,010	300000	630000	0	0	90,000	350,000	28,000,000
License Suspension$_{t\text{-}1 \text{ or more}}$	708,010	0.028	0.164	0	0	0	0	1
License Reinstatement$_{t\text{-}1 \text{ or more}}$	708,010	0.007	0.082	0	0	0	0	1
Tenure in Years	708,010	21.00	5.47	10	17	22	26	29
Graduation Cohort	708,010	1983.17	4.65	1980	1980	1980	1990	1990

TABLE 4
Logit Models: Predicting Fraud as a Function of Substance Abuse

Table 4 reports logistic panel regression models that test whether a doctor receiving professional sanctions for substance abuse predicts workplace fraud. Observations are at the doctor-year level. Z-statistics are in brackets below odds ratios. Standard errors are clustered at the doctor level. Statistical significance at the p<0.01 level is denoted by *.

Logit Model: Dependent Variable = 1 if Doctor Commits Fraud in year t	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Substance Abuse Sanction$_{t\text{-3 or more}}$	1.31							0.92
	[0.78]							[-0.20]
Substance Abuse Sanction$_{t-2}$		2.31						1.1
		[1.50]						[0.12]
Substance Abuse Sanction$_{t-1}$			3.83*					0.73
			[3.13]					[-0.52]
Substance Abuse Sanction$_{t}$				42.30*				44.68*
				[11.97]				[9.27]
Substance Abuse Sanction$_{t+1}$					9.55*			2.24
					[5.01]			[1.42]
Substance Abuse Sanction$_{t+2}$						2.18		0.47
						[0.80]		[-0.73]
Substance Abuse Sanction$_{t\text{+3 or more}}$							0.94	0.38
							[-0.10]	[-1.56]
Fraud Sanction$_{t\text{-1 or more}}$	4.10*	4.07*	4.11*	4.48*	4.17*	4.07*	4.06*	4.59*
	[3.87]	[3.83]	[3.84]	[3.66]	[3.85]	[3.84]	[3.85]	[3.82]
Sex Offense Sanction$_{t\text{-1 or more}}$	1.02	1.02	1.03	1.05	1.03	1.02	1.01	1
	[0.02]	[0.03]	[0.03]	[0.06]	[0.04]	[0.02]	[0.02]	[-0.00]
Unprofessionalism Sanction$_{t\text{-1 or more}}$	1.83	1.79	1.81	1.92	1.8	1.79	1.79	1.91
	[2.04]	[1.99]	[2.04]	[2.16]	[1.99]	[1.99]	[1.98]	[2.10]
Criminal Sanction$_{t\text{-1 or more}}$	1.74	1.68	1.66	1.44	1.71	1.76	1.77	1.55
	[1.32]	[1.20]	[1.18]	[0.75]	[1.25]	[1.33]	[1.35]	[0.91]
Malpractice Sanction$_{t\text{-1 or more}}$	1.27	1.26	1.29	1.57	1.28	1.23	1.22	1.53
	[0.75]	[0.72]	[0.80]	[1.36]	[0.77]	[0.65]	[0.64]	[1.25]
Ln(1+# Malpractice Lawsuits Settled)	2.52*	2.52*	2.53*	2.62*	2.53*	2.51*	2.51*	2.59*
	[6.89]	[6.90]	[6.92]	[6.92]	[6.92]	[6.89]	[6.88]	[6.83]
Ln(1+Cum. Malprac. Settl. $)	1.01	1.01	1.01	1	1.01	1.01	1.01	1
	[0.54]	[0.52]	[0.49]	[0.17]	[0.47]	[0.54]	[0.55]	[0.20]
License Suspension$_{t\text{-1 or more}}$	7.01*	7.15*	6.78*	5.29*	7.02*	7.36*	7.41*	5.47*
	[6.63]	[7.12]	[6.88]	[5.52]	[7.02]	[7.24]	[7.26]	[5.45]
License Reinstatement$_{t\text{-1 or more}}$	0.82	0.84	0.85	0.69	0.81	0.85	0.86	0.7
	[-0.65]	[-0.58]	[-0.54]	[-1.19]	[-0.71]	[-0.55]	[-0.51]	[-1.11]
Ln(Tenure in years)	0.96	0.99	1.02	1.32	1.02	0.97	0.96	1.28
	[-0.07]	[-0.01]	[0.04]	[0.52]	[0.03]	[-0.05]	[-0.07]	[0.46]
1990s Graduation Cohort	1.15	1.15	1.16	1.24	1.16	1.15	1.15	1.23
	[0.45]	[0.47]	[0.49]	[0.72]	[0.50]	[0.47]	[0.46]	[0.70]
Constant	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*	0.01*
	[-5.58]	[-5.63]	[-5.69]	[-6.06]	[-5.68]	[-5.59]	[-5.58]	[-6.00]
Observations	708,010	708,010	708,010	708,010	708,010	708,010	708,010	708,010
Pseudo R^2	0.0811	0.0814	0.0826	0.108	0.0842	0.081	0.0809	0.109

TABLE 5
2×2: Substance Abuse Sanction$_t$ × Fraud Sanction$_t$

Table 5 presents a 2×2 cross-tabulation of our dependent variable (Fraud Sanction$_t$) and the most influential test variable identified in Table 4 (Substance Abuse Sanction$_t$). This table also presents a Fisher's Exact Test to determine whether the fraud rate of 3.4% in the treatment sample (Substance Abuse Sanction$_t$=1) is statistically distinguishable from the fraud rate of 0.03% in the matched control sample (Substance Abuse Sanction$_t$=0).

Level of observation: Doctor-year		Fraud Sanction$_t$		
		No	Yes	Total
Substance Abuse Sanction$_t$	No	707,190 (99.97%)	199 (0.03%)	707,389
	Yes	600 (96.6%)	21 (3.4%)	621
	Total	707,790	220	708,010

Fisher's Exact Test: Pr(Fraud$_t$=1 |Substance Abuse Sanction$_t$=1) = Pr(Fraud$_t$=1 | Substance Abuse Sanction$_t$=0)
P-value (2-tailed) <0.001

TABLE 6
Rare Event Logit Models: Predicting Fraud as a Function of Substance Abuse

Table 6 reports rare event logistic panel regression models that test whether a doctor receiving professional sanctions for substance abuse predicts workplace fraud. Observations are at the doctor-year level. Z-statistics are in brackets below odds ratios. Standard errors are clustered at the doctor level. Statistical significance at the $p<0.01$ level is denoted by *. The full battery of control variables used in Table 4 are included in these models, but suppressed from the output.

Rare Event Logit Model: Dependent Variable = 1 if Doctor Commits Fraud in year t								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Substance Abuse Sanction$_{t\text{-}3 \text{ or more}}$	1.35							0.95
	[0.87]							[-0.12]
Substance Abuse Sanction$_{t-2}$		2.58						1.19
		[1.70]						[0.21]
Substance Abuse Sanction$_{t-1}$			4.10*					0.75
			[3.30]					[-0.46]
Substance Abuse Sanction$_{t}$				42.50*				45.36*
				[11.99]				[9.31]
Substance Abuse Sanction$_{t+1}$					10.41*			2.4
					[5.20]			[1.54]
Substance Abuse Sanction$_{t+2}$						3.54		0.72
						[1.30]		[-0.32]
Substance Abuse Sanction$_{t+3 \text{ or more}}$							1.19	0.47
							[0.25]	[-1.23]
Other Control Variables Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	708,010	708,010	708,010	708,010	708,010	708,010	708,010	708,010
Pseudo R^2	0.0811	0.0814	0.0826	0.1080	0.0842	0.0810	0.0809	0.1090

TABLE 7
Logit Models using a Coarsened Exact Matched (CEM) Sample: Predicting Fraud as a Function of Substance Abuse

Table 7 reports logistic panel regression models estimated using CEM matched samples that test whether a doctor receiving professional sanctions for substance abuse predicts workplace fraud. Observations are at the doctor-year level. Z-statistics are in brackets below odds ratios. Standard errors are clustered at the doctor level. Statistical significance at the p<0.01 level is denoted by *. The full battery of control variables used in Table 4 are included in these models, but suppressed from the output.

CEM Matched Sample Logit Model: Dependent Variable = 1 if Doctor Commits Fraud in year t							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Substance Abuse Sanction$_{t\text{-}3\text{ or more}}$	2.13						
	[1.91]						
Substance Abuse Sanction$_{t-2}$		3.32					
		[2.05]					
Substance Abuse Sanction$_{t-1}$			2.27				
			[1.39]				
Substance Abuse Sanction$_{t}$				50.29*			
				[10.32]			
Substance Abuse Sanction$_{t+1}$					1.25		
					[0.29]		
Substance Abuse Sanction$_{t+2}$						1	
						[0.01]	
Substance Abuse Sanction$_{t+3\text{ or more}}$							1
							[0.01]
Other Control Variables Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	680,661	365,773	429,951	676,432	673,187	669,692	689,829
Pseudo R^2	0.1190	0.0365	0.0234	0.1060	0.0969	0.1320	0.0617