Does Performance Pay Increase Alcohol and Drug Use?

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Using U.S. panel data on young workers, we demonstrate that those who receive performance pay are more likely to consume alcohol and illicit drugs. Recognizing that this likely reflects worker sorting, we first control for risk, ability and personality proxies. We further mitigate sorting concerns by introducing worker fixed effects, worker-employer match fixed effects and worker-employer-occupation match fixed effects. Finally, we present fixed effect IV estimates. All of these estimates continue to indicate a greater likelihood of substance use when a worker receives performance pay. The results support conjectures that stress and effort increase with performance pay and alcohol and drug use are a coping mechanism for workers.

Keywords: Performance Pay; Alcohol; Drugs; Sorting

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1. Introduction

Performance pay can increase productivity by aligning the interests of workers and firms. It can also serve to attract the best talent. Indeed, both survey and experimental evidence support these claims.[1] Yet, performance pay can also create unintended costs borne by workers, firms and society. These include reductions in product quality, reduced maintenance, wasted materials and failure to share valuable information (Freeman and Kleiner 2005). Perhaps most prominent among these costs, ever since Adam Smith's discussion of piece rates, is the risk of reduced worker health.[2] This reduction in health is, in part, because of higher work-related stress. Increased work stress due to performance pay may lead to increased consumption of alcohol and illicit drugs. Despite a sizeable literature on the health consequences of performance pay, the conjecture that performance pay increases alcohol and illicit drug use remains unexplored. This is surprising both because the medical literature sees work stress as a cause of alcohol and drug use and because of the enormous societal costs associated with alcohol and drugs.

We use broad US survey evidence on a cohort of younger workers to confirm a close association between performance pay and substance use. We demonstrate that for alcohol and the two classes of illicit drugs (marijuana and hard drugs) the rate of use is higher among, performance pay workers even after controlling for demographic characteristics, occupation and industry. We recognize that this may reflect sorting on ability or risk preferences. The same workers with low risk aversion who are attracted to alcohol and drugs will also be attracted to performance pay (Grund and Sliwka 2010). Thus, much of our contribution consists of eliminating the likely

[1] On productivity see, among others, Banker et al. 1996; Lazear 2000; Bandiera et al. 2005; Gielen et al. 2010; Heywood et al. 2011 and on sorting for talent see Lazear 2000; Cadsby et al. 2007; Dohmen and Falk 2011; Shaw 2015.

[2] "Workmen. . . when they are liberally paid by the piece, are very apt to overwork themselves, and to ruin their health and constitution in a few years (Smith 1776, p. 83)."

suspects of statistical contamination and showing that the correlation strongly persists. First, we include proxies for risk preferences, ability and personality incorporating sophisticated error structures. We also recognize a possible income effect in which higher earnings from performance pay increase substance use. Second, we use the survey's panel structure to hold constant time-invariant worker fixed effects that could include unmeasured risk preferences or ability. Third, we recognize that changes in unmeasured worker characteristics can lead to both job change (and so performance pay receipt change) and to a change in substance use. We respond by controlling for job match fixed effects. Thus, we examine the change in individual workers' substance use when their employer changes their performance pay status (even as they remain in the same detailed occupation). We also confirm that the pattern of use on the extensive margin is matched by count variable estimates on the number of times that substances are used over a given period, the intensive margin. We show that the pattern of elevated use persists when controlling for depressive moods of workers and that the pattern also persists in a fixed-effect IV estimate.

Thus, our study is the first to examine the relationship between performance pay and substance use. It takes very seriously the bias arising from the many dimensions of worker sorting and finds that those newly exposed to performance pay are more likely to consume both alcohol and drugs. This is timely evidence given the broad trend towards performance pay in the US (Lemieux et al, 2009) and ongoing concerns regarding the social cost of substance use.

Substance abuse disrupts families, workplaces and communities. The aggregate cost in lost earnings, diminished productivity, health expenditures and crime exceeds $442 billion per year in the United States.[3] Over 88 thousand deaths per year are associated with alcohol use, and the CDC (2016) claims the social costs of alcohol should add over two dollars to every drink served. The

[3] This reflects $249 billion per year in alcohol related costs (CDC 2016) and $193 billion per year in drug related costs (NDIC 2011).

US Justice Department puts the number of illicit drug users in the US at nearly 22 million and finds that illicit drugs account for over 1 million emergency room visits per year (NDIC 2011). Thus, alcohol and drugs are associated with substantial societal costs.

Employers broadly recognize these costs and their impact on firm performance. Thus, they test for drugs, have health insurance provisions that penalize risky behaviors and provide employee assistance programs connecting workers with treatment (see McGurie and Ruhm 1993). Yet, when setting compensation, other issues may be paramount and managers may not focus on these costs or recognize the link between compensation structure and substance use. Thus, our findings are important. First, they suggest that the benefits to firms of increased productivity and talent may be partially offset by higher absence and health insurance costs associated with substance use. Second, the associated costs are unlikely to be borne entirely by firms as spillovers into family and community seem likely. This may provide a rationale for public intervention to monitor and perhaps even regulate the use or intensity of performance pay. Third, the earnings return for performance pay (Seiler 1984; Parent 1999; Pekkarinen and Ridell 2008; Green and Heywood 2016) reflects not only productivity gains but may, in part, be a compensating differential for stress and the associated risk of alcohol and drug use.

We do not claim that performance pay makes the typical worker worse off.[4] Nor do we claim that firms fail to benefit from performance pay (such as from increased productivity). Most workers exposed to performance pay do not newly begin substance use but a few percent of them do. Thus, we show that the likelihood of substance use increases under performance pay and that this more modest statement should be part of any overall evaluation.

[4] Indeed, using UK data Green and Heywood (2008) show that as measured by subjective job satisfaction, performance pay workers, on balance, remain more satisfied.

The next section sets the context by summarizing the empirical evidence on the relationship between performance pay and worker health. We stress the relatively few studies that go beyond workplace injury to examine longer-term health and stress. We also review the evidence on work stress and substance use. Section 3 presents our data being careful to describe the important proxies and the panel structure. Section 4 describes our empirical approach. Section 5 presents our results confirming the link between performance pay and alcohol/drug use. Section 6 presents our IV estimate and explores heterogeneity. The final section provides a summary.

2. Motivation and Previous Research

A growing literature tests whether workers tradeoff their health in pursuit of the rewards associated with performance pay. Some of this reflects case studies in occupational health. Thus, transitioning to piece rates is associated with higher accident rates among Swedish loggers (Sundstroem-Frisk 1984) and Canadian tree cutters dangerously over-exert themselves when a forest area makes for easy money (Toupin et al. 2007). Similarly, piece rate workers in India's fertilizer industry face a higher risk of industrial accidents than time rate workers (Saha et al. 2004). Monaco and Williams (2000) show that US truck drivers paid by the mile are more likely to be in an accident and violate safety standards than those paid by the hour. Frick et al. (2013) show that a German steel plant experienced increased sickness absence after introducing production bonuses.

This emphasis on accidents carries over to economics literature using broad survey data. The underlying causation argues that performance pay generates increased exertion, the taking of fewer breaks, the taking of greater risks, and working too fast or working to the point of exhaustion. Performance pay increases the reward for these activities (DeVaro and Heywood 2017). The consequence is a greater risk of accident and workplace injury. Bockerman et al. (2012) examine a broad set of high-performance work practices in the Finnish Quality of Work survey that includes

performance pay and discover no relationship between this set and accidents. Yet, Bender et al. (2012) use the European Working Conditions Survey to show that piece rates are associated with an increased risk of workplace injury after controlling for an extensive set of controls, country fixed effects and error structures. Artz and Heywood (2015) use the 1979 NLSY to show that US blue-collar workers experience a higher risk of workplace injury when paid based on output. This persists despite worker fixed effects. DeVaro and Heywood (2017) show greater sickness absence and physical ailments (repetitive stress injuries and bone/joint ailments) among UK workers at firms using performance pay. They hold constant employer fixed effects. Less direct evidence comes from Freeman and Kleiner (2005) who indicate that piece rates are associated with higher worker compensation costs which largely reflect workplace injuries.

While these studies suggest performance pay changes worker behavior on the job, the determinants of alcohol and drug use may differ from those of industrial accidents.[5] Drug and alcohol use may change largely off the job and reflect a spillover from the increased pressure and stress at work (Grunberg et al. 1998).[6] Thus, the medical literature focuses on work pressure, work stress and the associated alcohol and drug use. This view often includes stress not only within the work role but also stress integrating work and family roles (Frone 1999). It identifies alcohol and drugs as coping mechanisms associated with the stress of negative work as well as home events (Carney et al. 2000). Moreover, Frone (2008) confirms a role for two specific work stressors, work overload and job insecurity. This is telling as performance pay is designed to increase earnings insecurity by putting pay at risk and for workers to respond with greater effort (Gneezy and Rey-Biel 2014; Pencavel 2015).

[5] Which is not to say the two need be unrelated as Kaestner and Grossman (1998) present evidence on the influence of drug use on workplace accidents and injuries.
[6] Rohleder (2014) reviews the medical literature on the effects of stress arguing that constant chronic psychosocial stress that persists over time can be psychologically and physically damaging.

Alcohol and drug use should then be thought of as a potential response to the stress, uncertainty, time conflict and effort associated with performance pay. While not focusing on performance pay, economists have examined work stress and substance use. Dee (2001) confirms that higher rates of state unemployment increase both the use of alcohol and binge drinking even for those who remain employed. Moreover, while not focusing on substance use, Foster and Rosenzweig (1984) show that agricultural workers paid by the piece expend enough extra effort that their physical health is measurably worse. Others have moved beyond just physical health.

Davis (2016) examines both physical and *emotional* health in a large survey of workers in Vietnamese garment factories. She controls for each factory's success in occupational health compliance and reports that piece rate workers report both lower physical and emotional health. Indeed, piece rates provided the most consistent and important of all demographic and factory-level variables in determining emotional health. Bender and Theodossiou (2014) demonstrate a larger hazard of falling out of good self-reported health for British workers receiving a very broad measure of performance pay (including bonuses, commissions and other more common white-collar performance pay). Importantly, for our purposes, they match this with similar results for the hazard of reporting anxiety. Like stress, this might be thought of as a precursor to alcohol or drug use. Confirming such survey data, Cadsby et al. (2016) use laboratory experiments to demonstrate that performance pay increases stress among the risk averse. Allan et al. (2017) provide much more sophisticated experimental evidence showing not only do those on performance pay self-report higher stress but that they have objectively higher stress as measured by cortisol hormone levels.

In the study closest to ours, Dahl and Pierce (2019) take for granted that stressful work causes coping through substances. They link performance pay for Dutch firms to the medical prescriptions of their workers. They conclude that the adoption of performance pay generates a four to six

percent increase in the usage of one broad class of anti-anxiety drugs and in the use of SSRI anti-depressants. This is observed almost exclusively in men and for those older than fifty. Thus, they argue that performance pay induces stress and anxiety which spills over to harm daily mental health and leads to increased prescriptions for the associated pharmaceuticals.

We bring alternative data to bear. We do not examine drug prescriptions but self-reports of alcohol and drug use. We examine a representative sample of younger workers in the US. None of our workers have reached age fifty over the years we examine. As only half of all US private industry employees participate in employer-sponsored healthcare benefit plans, it should not be assumed that our sample has low cost access to physicians and legal drug prescriptions as in the Netherlands. Moreover, participation in employer health plans is far lower than half among workers who are younger and who earn less (Wile 2017). Thus, the connection between work stress and substance use may be particularly strong in the US and in our sample. While we do not have access to respondent's legal drug prescriptions, we will control for the presence of health insurance coverage to account for other avenues of coping. We anticipate that health insurance should be associated with lower use of alcohol and illicit drugs.

3. Data and Variables

We draw our data from the National Longitudinal Survey of Youth 1997 (NLSY). The NLSY contains information on payment methods, self-reported measures of alcohol and drug use and a strong variety of worker controls. The NLSY follows a single cohort that may not be fully representative of the population and began interviewing in 1997 when all respondents were in their teen-age years. Since a variety of mechanisms impact drug and alcohol use at very young ages, we limit our analysis to NLSY waves consisting of respondents all of whom are at least 18 years

of age. Thus, we begin with wave 2002 and end with 2011[7]. After removing the military and those with incomplete information, our marijuana and alcohol samples consist of 62425 observations and our hard drugs sample is 61673 observations.

We use self-reported measures of alcohol and drug use indicating whether or not individuals consumed "marijuana (pot/weed)" or alcohol in the last 30 days, and whether individuals consumed "drugs like cocaine, crack, heroin, or crystal meth, or any other substance not prescribed by a doctor, in order to get high or achieve an altered state since the date of the last interview" (roughly one year ago)[8]. We recognize the potentially broad set of drugs in this and denote it as hard drugs for convenience. Appendix A1 contains substance use proportions; 4.6% of respondents reported using hard drugs since the last interview while 16.8% and 66.3% used marijuana and alcohol respectively in the last 30 days.

Much of the research on substance use depends on self-reported measures. Yet, potential measurement error can exist. Hoyt and Chaloupka (1994) find that interviewing circumstances and who else might be in the room can influence self-reports. Yet, the overall reliability and consistency of self-reported measures of substance use have typically proven very high (O'Malley et al. 1983, Simons et al. 2015) and they remain widely used.

The NLSY identifies five forms of performance pay: tips, commissions, bonuses, incentive pay and a small "other" category. It is not made clear whether these are individual or group oriented nor whether bonuses and incentive pay are objectively set (by formula) or determined by the subjective judgement of a supervisor. In the absence of clear guidance, we combine all five

[7] The wave after 2011 (2013) does not include the marijuana and hard drugs use measures. Although the 2015 wave reintroduces these measures, we chose to omit the wave both because of the 4 year time span since 2011 and because the period since 2011 has seen growing legalization of marijuana among US states.
[8] There is unfortunately no 30-day equivalent for drugs in the survey. Similarly, while the drug measure indicates may types of drugs, different types of alcohol (beer, wine, spirits) are not identified.

into one measure of performance pay but experiment with alternatives. Roughly 21% of respondents report receiving at least one type of performance pay. Our ultimate examination of narrow matches of worker, employer and occupation helps alleviate concern that specific jobs or employers are associated with both a specific type of performance pay and substance use.[9]

The survey allows us to control for demographic variables such as gender, race, age, education, region of residence and marital status. We also control for job characteristics such as usual hours worked per week and the industry and occupation categories using the 2002 Census of Industrial and Occupational Classification Codes. As discussed, we also include a dummy variable indicating the worker is covered by health insurance (see descriptive statistics in Appendix Table A1).

We recognize that unmeasured characteristics may correlate with both substance use and sorting into jobs with performance pay. In response we include proxies for risk attitudes and worker ability. The risk proxy is available only in a single wave but we recognize the broad consistency of risk attitudes over modest periods of time as supported by Chiappori and Paeilla (2011) and Brunnermeier and Nagel (2008). The 2010 NLSY wave asks respondents, "are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Rate yourself from 0 to 10, where 0 means 'unwilling to take any risks' and 10 means 'fully prepared to take risks.'" The mean of 5.6 suggests workers are, on average, relatively risk neutral, but preferences are dispersed as one standard deviation around the mean gives a range of 3.06 to 8.13.

In the 1999 NLSY wave all respondents completed the Armed Services Vocational Aptitude Battery (ASVAB), a commonly used ability measure like an IQ test (Coyle, 2018). We use the worker's percentile ranking in combined math knowledge, arithmetic reasoning and verbal comprehension. The mean ranking in our sample is slightly below 50 (48.5) due to omitted

[9] An example of such a concern would be that sales jobs are associated with commissions and with drinking with customers.

military observations and those with incomplete information. We normalize both this ability measure and the earlier risk measure fitting a cumulative normal so that the unit of measure is a standard deviation in the underlying variable. This changes no results but aids interpretation.

As additional controls, we include an eight-item personality battery that comes from the 2002 wave and is a variation on the Big Five. Personality may both influence the likelihood of substance use (Walton and Roberts 2004) and of receiving performance pay (Heywood et al. 2017).

Finally, as the measures above do not vary across waves, we include the average hourly wage. While the basic pattern of our results in no way depends on including the wage, it does vary by wave and is well known to reflect both ability and risk preference. We understand that this interpretation is not unique as a wage influence may also reflect an income effect for normal goods. Moreover, wages are obviously endogenous with performance pay. Yet, the anticipated bias works against our hypothesis as one would anticipate that its inclusion would bias down the role of performance pay[10]. Again, we see it both as a potential proxy and as capturing the income effect but note that its inclusion is not critical.

4. Empirical Approach

We examine the role played by performance pay in increasingly complete specifications of the determinants of alcohol and drug use. Our estimates can be expressed as variants on the equation:

$$Y_{it}^{*} = \alpha PRP_{it} + \beta' \boldsymbol{X_{it}} + u_t + \varepsilon_{it} \qquad (1)$$

where *i* and *t* index workers and survey waves. In all cases, the likelihood of using alcohol or drugs is an unobserved latent variable Y_{it}^{*} that is proxied by the dichotomous NLSY indicator assumed

[10] As earnings are positively correlated with performance pay, their inclusion presumably robs some of performance pay's influence on alcohol and drug use. We will explore this in depth when considering potential income effects.

to be 1 above threshold k: thus, Y_{it} = 1 if $Y_{it}^{*} > k$ and $Y_{it} = 0$ otherwise. Logit is chosen to allow easy comparison with the "conditional" or fixed effect logits that control for time-invariant heterogeneity (Long 1997). This fixed effect estimate is preferred as it does not suffer from the incidental parameter issue common in non-linear fixed effect estimates.[11] To facilitate comparison, we present both the average marginal effects and the log-odds for the pooled estimates. All estimates use sample weights and cluster errors by worker to account for repeated observations.

The term $u_t$is a wave fixed effect that may capture variation in substance use associated with overall economic conditions (Carpenter et al. 2017). $\boldsymbol{X}$ is a vector of worker and job characteristics including the constant. PRP indicates receipt of performance pay, and α is our parameter of interest. We estimate (1) separately for each type of substance use. Initially, we focus on use, but in extensions consider measures of intensity of use and the number of substances used.

As described, sorting threatens any causal interpretation of α. Two sorting dimensions seem of the most concern. First, and perhaps most critical, risk tolerant workers sort into performance pay (Curme and Stefanec 2007; Grund and Sliwka 2010; Cornellissen et al. 2011). This follows naturally as the purpose of these contracts is to shift risk to workers. At the same time, there is a well-established link between individual risk preferences and alcohol and drug use (Lundborg and Lindgren 2002; Blondel et al. 2007; Dave and Saffer 2008)[12]. Thus, sorting on risk would generate upward bias in naïve estimates of the influence of PRP on substance use. Second, as emphasized in the introduction, more able workers capture a return on their ability by sorting into performance pay (Lazear 2000). While not unambiguous, there also appears to be a correlation between ability

[11] Although we note that probit estimates of the pooled estimates return very similar results in terms of the size and significance of the key variables.
[12] Dave and Saffer (2008) show evidence that *both* the probability of using alcohol and the amount consumed by users are 6 – 8% higher among risk-tolerant individuals.

and substance use. Batty et al. (2008) show that those with higher childhood mental ability scores have an increased prevalence of drinking in adulthood. Similarly, White et al. (2012) shows that higher ability scores correlate (after including controls) with a greater likelihood of illicit drug use. Again, sorting on ability would generate upward bias in our estimates.

In response, we first utilize the strengths of the NLSY data that include proxies for both ability (ASVAB) and risk attitudes. These proxies likely mitigate bias arising from sorting. As discussed, we also include wages as a further control. While this inclusion is not critical, it is anticipated that higher wages may proxy for greater ability and risk tolerance as well as reflect income effects. We also explore the role of personality traits as critical dimensions of sorting.

We then go beyond this to examine estimates including worker fixed effects. These hold constant time invariant individual influences that may include both risk preferences and worker ability unmeasured by our proxies. This may be satisfactory as some researchers emphasize the relatively fixed nature of risk preferences. Sahm (2012 p. 1) followed a panel of US respondents over eleven years noting that "while risk tolerance changes modestly with age and macroeconomic conditions, persistent differences across individuals account for over 73% of the systematic variation." Indeed, the typical search for changes in risk preferences involves studying the consequences of dramatic natural disasters and even here a large portion of the population shows persistent risk preferences (Hanaoka et al. 2017). The same worker fixed effect estimates will also account for other time invariant personality traits beyond risk aversion. To the extent that personality traits are highly stable during working ages as demonstrated by Cobb-Clark and Schurer (2012, 2013), sorting on personality will be held constant.

Nonetheless, we recognize that changes might happen. A change in risk preferences might cause workers to both change jobs (and so change performance pay receipt) and change their

substance use.[13] Controlling for individual fixed effects provides no defense against this potential threat. As a response, we identify specific matches between workers and employers. We use these to examine the determinants of drug and alcohol use with match fixed effect estimates. This specification excludes workers who change risk preferences and so change employer. The influence of such sorting is eliminated by focusing on workers who remain with their employer and examining their change in drug and alcohol use as their employer changes performance pay policy. While this substantially narrows the sample of workers, we will show it remains largely representative of the broader sample. It will also confirm estimates on the broader sample and continue to show that sorting by workers does not explain the increased use of drugs and alcohol among workers receiving performance pay.[14]

We also undertake two further examinations. First, we hold constant matches of worker with both employer and detailed occupation. This eliminates sorting across occupations within an employer. Second, we present fixed effect instrumental variable estimates. While our primary concern is eliminating threats to identification caused by sorting, time varying influences may drive both the employer decision to adopt performance pay and substance use by workers.

5. Results

Table 1 reports logit estimates of the relationship between performance pay receipt and marijuana, hard drugs and alcohol use, respectively. In each case, the likelihood of use decreases with age and marriage. Similarly, the likelihood of reported use is lower for women, Blacks and Hispanics (confirming Chen and Jacobsen, 2012). Education and hours of work are negatively associated

[13] Dohmen et al. (2017) demonstrate that individuals become slowly less risk tolerant with age.
[14] We recognize a possible more complicated, and we think counter-intuitive, form of sorting. Firms could change their performance pay policy to reflect the risk preferences of their workers. While possible, this obviously implies that the workers initially sorted into their employer in direct opposition to their own risk preferences.

with marijuana use but positively associated with alcohol use. Health insurance positively predicts alcohol use (perhaps an income effect) but negatively predicts hard drug use as anticipated.

The main estimates of interest reveal large, positive and statistically significant, relationships between performance pay and all types of substance use. The odds ratio (in brackets) indicate that holding other determinants constant, performance pay workers have odds that are 29% higher for marijuana use, 35% higher for hard drugs use and 45% higher for alcohol consumption. These reflect average marginal effects of 0.035 for marijuana, 0.015 for hard drugs and 0.072 for alcohol.

INSERT TABLE 1

These are substantial marginal effects but remain in line with related studies. Dee (2001) for example reports that a six-percentage point increase in the state unemployment rate is associated with a marginal effect of 0.024 in the increase in alcohol use among the full sample of employed and unemployed. The odds coefficients deserve careful interpretation as they will be reported for the fixed effect models. If one takes the average alcohol use of those not on performance pay, 0.64, the odds ratio is 1.78 (0.64/0.36). The odds ratio coefficient implies that this increases by a factor of 1.45 to 2.58 for those on performance pay. This new odds ratio corresponds to an alcohol probability use of 0.72. The resulting increase of 0.08 is very similar to the average marginal effect. Identical operations with other odds ratios gives an increase of 0.037 in the marijuana use probability and an increase of 0.014 in the hard drug use probability. Thus, the seemingly large odds ratio coefficients closely correspond with the average marginal effects.[15]

As highlighted, sorting on ability and risk threatens interpretation of Table 1. Table 2 adds the three proxies, self-reported risk tolerance, ASVAB and earnings. The reduced sample size in

[15] The mean usage of marijuana among those not on performance pay is 0.160 and that for hard drugs is 0.042.

Table 2 comes from requiring that each respondent be in 1999 (to get the ASVAB) and in 2010 (to get the risk proxy). Thus, as a check we first confirmed that the key performance pay results in Table 1 carry over to the reduced sample – they do. For brevity Table 2 hides the coefficients for most other covariates but we note that adding the proxies eliminates the positive partial correlation of health insurance with alcohol use while retaining the significant negative partial correlations of health insurance with the use of the two illicit substances.

Two additional points are worth noting about the role of health insurance. First, there exist only modest differences in results if employer provided health insurance replaces all forms of health insurance in the estimation. Second, having said that, if one divides the sample by employer provided health insurance, those with such insurance have smaller responses to performance pay and significantly so for alcohol use. This hints at the possible substitution of prescribed drugs and substance use. These estimates are available upon request.

As anticipated, the proxies for ability and risk preference have positive, large and statistically significant, influences on substance use. A one standard deviation increase in the ability proxy generates average marginal effects of 0.041 for marijuana, 0.018 for hard drugs and 0.058 for alcohol. A one standard deviation increase in the risk tolerance proxy generates average marginal effects of 0.023 for marijuana, 0.011 for hard drugs and 0.024 for alcohol. Again, the large and consistent marginal effects are noteworthy and suggest sorting on ability and risk tolerance. The log wage measure proves a significant positive partial correlate of alcohol use and a negative partial correlate of illicit drug use.

While the proxies play important roles, their inclusion does little to change the relationship between performance pay and substance use. The new magnitudes from the odds ratio (again shown in brackets) indicate 28 percent higher odds for marijuana use, 27 percent higher odds for

hard drug uses and 41 percent higher odds for alcohol consumption relative to those on time rates. These measures and the associated marginal effects show only modest changes. This provides a first indication of the durability of the association and hints that this relationship may not simply reflect sorting on ability and risk preferences, as important as those seem to be.

INSERT TABLE 2

In additional estimates we altered the measurement of earnings. The current wage measure does not include earnings specifically associated with performance pay. Unfortunately, we cannot completely isolate these earnings as the question asks for additional earnings associated with performance pay *or* overtime. Yet by adding this additional component and creating a "full average wage" we may more properly isolate the income effect. This wage measure seems especially likely to be collinear with performance pay and we present the estimates in Appendix Table A2. Using the new measure does not change the results. The marijuana coefficient is unchanged, the hard drugs coefficient goes very slightly up and that for alcohol goes slightly down. As explicitly controlling for the income associated with performance pay does not change results, it seems unlikely that the performance pay influence primarily reflects income effects.[16]

The personality traits are examined in the on-line appendix. Both Tables 1 and 2 are reproduced adding 8 separate personality trait indicators. These trait indicators are a variant on the big five. The disorganized are more likely to use substances and the thorough are less likely to

[16] We have used this alternative full earnings measure in all the estimates in this paper. They are available upon request but are remarkably unchanged throughout. We also tried to replace the indicator of performance pay with this measure of the wages associated with performance pay and overtime. It was also typically a positive and significant determinant of substance use but failed to be robust in some of the narrower fixed effect estimates perhaps because of the measurement error associated with the included overtime earnings.

use substances. The trustful are more likely to drink. Yet, none of these associations change the role of performance pay.

Table 3 further examines this seeming stability by exploiting the panel structure of the NLSY. The first set of estimates introduce worker fixed effects that hold time invariant characteristics constant, thereby measuring the influence of within worker changes in the performance pay. These estimates reflect the smaller sample of workers who change performance pay status. Nonetheless, there remain 5,615 worker transitions into performance pay and a roughly similar 5,450 worker transitions out of performance pay. As the risk preference and ability proxies drop out of the fixed effect estimate, workers in the panel need not be in both 1999 and 2010.

The left panel presents the worker fixed effects estimate and we note that health insurance is now a significantly negative determinant of alcohol use. Also, the only remaining significant role for wages is as a positive determinant of alcohol use. Critically, the positive relationship between performance pay and substance use remains but is reduced in magnitude. The odds ratio (now shown as the primary entry) indicates a 16 percent odds ratio increase for marijuana use, 21 percent increase for hard drug use and 22 percent increase for alcohol use. These correspond to increases of 0.021 in the probability of marijuana use, 0.008 in the use of hard drugs and 0.045 in the use of alcohol. All three estimates remain highly significant and sizable but clearly indicate a role for time invariant characteristics not captured by our ability, risk preference or personality proxies. Nonetheless, performance pay remains associated with substance use. Interestingly, adding three-digit occupational controls causes no change in the pattern of results for the worker fixed effects.[17]

INSERT TABLE 3

[17] These are available upon request.

To this point, we have focused on the incidence of consumption. Appendix Table A3 reports results where the dependent variable is the frequency of use. Each of the substance use questions asks those who report positive use to indicate how often they have used the substance (within the last year for hard drugs and within the last month for marijuana and alcohol). These counts are estimated in Poisson specifications with worker fixed effects. The choice of Poisson reflects the absence of the incidental parameter problem (and the associated bias) known to exist in, for instance, Tobit (Greene 2004).[18] These confirm a positive link between substance use and the frequency of substance use, although the estimate for hard drugs is relatively imprecise. The coefficients represent the expected increase in the log count. Thus, the performance pay coefficient for marijuana of .083 corresponds with an 8.7 percent increase in frequency of use. While most of our concern remains with the use itself, the extent of use reflects broadly similar patterns.

The change in performance pay receipt identifies the worker fixed effect estimates just presented for both substance use and the extent of use. Yet, as suggested, a change in risk preference or personality might lead a worker to a new employer with a more compatible performance pay policy and to changes in substance use. We examine this by limiting the source of identification to an employer's change in performance pay for continuing workers. We identify every match between employer and worker and use these as fixed effects. Thus, the estimate comes from variation in performance pay and in substance use within such a match. This excludes the possibility that the worker changes employer in search of a preferred performance pay policy. There remain 2832 cases in which a worker moved into performance pay with their current employer and 2369 in which a worker moved out of performance pay with their current employer.

[18] As a check, we did perform Tobit estimates as a simple form of a double hurtle model. These continue to show a large and significant coefficient for performance pay and are presented in the on-line appendix Table OA2.

The second panel of Table 3 shows that these results follow earlier estimates, and if anything, reveal a larger effect of PRP on substance use. The results indicate a 29 percent increase in the odds ratio for marijuana use, a 26 percent increase in the odds ratio of hard drug use and a 34 percent increase in the odds ratio alcohol use. These point again to durability. In sum, the results in Table 3 indicate that the relationship between PRP receipt and marijuana, hard drugs and alcohol use persist despite worker sorting on time fixed unobserved worker characteristics, or worker sorting across employers.

Workers may also react to performance pay by using more than one substance. This can be viewed as a count variable, not the number of uses of a given substance but, instead, the number of substances used. At any point respondents may use zero to all three substances. Appendix Table A4 shows the progression of fixed effect estimates we have just been describing but estimated on the number of substances using Poisson. The number of substances clearly responds to performance pay. Workers are nearly 4 percentage points more likely to use another substance (an increase in the count) when assigned performance pay by their employer.

We hypothesize that drug and alcohol use reflect the stress and uncertainty of performance pay. This may be made more believable by identifying other lifestyle choices less likely to reflect such causation. We chose three lifestyle indicators to use as placebo tests. The first is smoking. This is another addictive substance but its pattern of starting and stopping differs dramatically and thus, it may not show the same relationship to performance pay. Smokers typically start before the working years we examine. More than 90 percent begin before age 18 and essentially all before age 25 (US Health and Human Services, 2012). Thus, there are essentially no smokers who start later in life and most attempts to stop end quickly in failure (US Health and Human Services,

2012).[19] Thus, smoking has long been an indicator of inherent risk preference when more direct measures are unavailable (Hersch and Viscusi, 1990; Barsky, 1997; Brown et al., 2006; Artz and Heywood 2015). Moreover, those that study determinants of smoking typically focus on teenagers and very young adults (Cawley et al. 2004). The second lifestyle indicator is sexual activity which may proxy risk preferences but seems less likely to respond to performance pay. The third lifestyle indicator is religiosity which again seems less likely to be caused by performance pay. The indicators for smoking and sexual activity ask whether respondents have engaged in these activities in the last month. The religiosity indicator identifies those engaging in at least daily prayer.

Appendix Table A5 presents the results. Performance pay emerges as a significant partial correlate with each indicator in the pooled estimates. It associates with a reduced probability of religiosity and an increased probability of smoking and sexual activity. Accounting for fixed effects generates a consistent but very much changed pattern. Regardless of whether we use simple worker fixed effects or match fixed effects, changing performance pay status plays no role in changing any of these lifestyle indicators. The magnitudes fall dramatically in the fixed effects and even the sign of association changes. Thus, many lifestyle choices may correlate with performance pay but merely reflect sorting. The use of our three substances does not merely reflect sorting.

Our earlier use of three-digit occupational controls suggests yet another dimension which could be held constant to reduce the role of self-sorting when examining substance use. Thus, we examine changes in performance pay status that happen for a given worker, with a given employer and within the same detailed occupation. This rules out workers who switch occupation with the same employer and where the occupational sorting influences substance use rather than the

[19] None of this denies that the amount of smoking among those already smoking might respond to stress and so to performance pay. Estimates in the on-line appendix Table OA3 present mixed results with frequently of use positively associated with performance pay in the pooled and worker fixed-effect but not in the worker-employer match fixed effect.

performance pay associated with that detailed occupation. Yet, this pushes the data as we have smaller sample sizes and even a few misclassified occupations could generate an errors-in-variables problem as workers self-select broadly similar but different occupational codes even as their job has remained identical overtime.

The estimates that examine changes within worker, employer and occupation return broadly similar results. The marijuana use estimate is 1.375 with a t-stat of 3.85. The alcohol use estimate is 1.123 with a t-stat of 1.83 and the hard drug use estimate is 1.119 with a t-stat of only 1.17. Thus, the point estimates of marijuana and alcohol use retain their size despite adding the additional requirement that detailed occupational codes remain identical.[20]

6. Robustness and Heterogeneity

This section continues examining the durability of the link between substance use and performance pay. First, we undertake an instrumental variable estimation while still focusing on the importance of sorting. Second, we explore the basic patterns within subsamples and when slightly varying our definition of performance pay. Third, we control for workers' depressive mood as performance pay has been shown to increase SSRI anti-depressant prescriptions (Dahl and Pierce 2019).

6.1 IV Estimation

While the fixed effect estimates control for time invariant characteristics, time varying influences may cause both the firm to offer PRP and substance use by workers. Thus, an external event causes the firm to switch to performance pay and it is that external event that induces stress among workers rather than performance pay. A first thought for such an event might be a heightened

[20] Again, the detailed estimates are available upon request.

chance of firm failure. Yet, performance pay is more often part of firm growth initiatives (Heywood and Jirjahn 2012). Moreover, while associated with poor performers leaving the firm (Lazear 2000), the contingent nature of performance pay tends to reduce employment swings. Williams (1999) shows no relationship between overall turnover and performance pay and O'Halloran (2012) shows *less* frequent layoffs among firms with performance pay. Yet, these points do not rule out that external events could drive our fixed effect estimates.

In response, we follow an instrumental variable (IV) strategy based on aggregation (for examples see Fisman and Svensson 2007; Lai and Ng 2004; Bilanakos et al. 2018 among others). This common strategy assumes that the extent of performance pay in an occupation reveals independent information about the odds that any individual worker in that occupation will receive such pay. Thus, the output of an occupation may be subject to easy observation increasing the share of workers receiving performance pay.[21] Simply put, a worker in a specific occupation is unlikely to receive performance pay if other workers in that occupation do not receive such pay. The identifying variable is the share of a worker's current three-digit occupation receiving performance pay lagged one year. Thus, we give up a year of data hoping to introduce independent variation that is assumed to allow the identification of causal direction and effect size.[22]

The estimation uses two stage least squares with dichotomous substance use still the dependent variable. The first stage has the potentially endogenous current performance pay measure of the worker as a function of all included variables plus the lagged and aggregated occupation measure. The second stage returns the instrumented value from the first stage to the estimate of substance use correcting the standard errors.

[21]It is easier to identify performance for a sales person or drill press operator than for an assembly line operator. The aggregated measure then indicates greater scope for provision in the first occupations than in the latter.
[22] The exclusion requirement necessitates that the aggregated measure from the previous year does not directly influence the individual worker's probability of substance use this year.

Yet, our emphasis on the importance of sorting requires that in addition to the IV we account for fixed effects. Our previous results strongly show that such sorting exists and that accounting for it is important. Table 4 shows the fixed-effect IV estimates.

INSERT TABLE 4

First, a weak instrument problem does not exist. Second, the endogeneity test emerges as highly significant but only for hard drugs. Despite giving up a year of data, controlling for fixed effects and using instrumental variable estimation, the pattern appears robust. Use of all three substances responds positively to the initiation of performance pay. The point estimates emerge as larger than equivalent estimates without the IV as shown in appendix Table A6. This suggests the likely presence of measurement error. Yet, overall the estimates in Table 4 remain of the same general magnitude of those in first panel of Table 3, two larger and one smaller. All three estimates are statistically significant at least at the five percent level. We take this as a reassuring indicator of robustness but recognize that the assumption of a single conditionally exogenous instrument cannot be directly tested. Thus, while the case for causation is not closed, the IV estimates support the general pattern of results.

6.2 Subsample Patterns

We now explore whether the role of performance pay differs in systematic ways across subsamples. We divided the full sample into those workers in the South and those not in the South. We also divided it between those with more than 12 years of education and those with 12 or less. We divided it into those in Finance, Insurance and Real Estate and those not. We divided it into those in food and beverage serving and those not. We divided it into those in Medical professions

and those not. In each case we think these might be meaningful divisions that would show patterns of heterogeneity. For example, those in medical professions have easier access to drugs but may face greater regulations over drug use. Appendix Table OA4 summarizes the results. While these are simply the pooled cross-sections of Table 2, the stability is remarkable. Virtually, every subsample shows a role for performance pay (although small sample size sometimes causes a loss of significance). The differences across the divisions are typically not dramatic. Perhaps the most dramatic is that food and beverage service workers show larger responses.[23] Also, while alcohol use in the South is lower, the response to performance pay in the South is larger.

In Table 5 we summarize estimations also based on Table 2 but which divide the sample into four race and gender groups. The clear pattern across is that non-white men are far less responsive (and, indeed, unresponsive for two substances) when compared with the remainder of the sample.[24]

INSERT TABLE 5

Findings from occupational health demonstrate that minorities have greater average work-related stress and poorer health and that this is often associated with perceived discrimination (Wadsworth et al. 2007; Capasso et al. 2016; Johnston and Lordan 2012). Thus, it may be that work stress associated with performance pay plays a smaller role in overall work stress and may be less of a determinant of substance use for minority males. Alternatively, introducing performance pay may bring stress associated with uncertainty and effort but be offset by reduced stress regarding workplace discrimination. In this view, performance pay if tied to easily

[23] Unfortunately, the relatively small number of workers who stay within this division and change performance pay do not allow meaningful fixed effect estimates within the food and beverage workers.
[24] Indeed, the pattern of significant results largely carries over to the individual fixed effect estimates but dissipates due to small sample size in the job match fixed effects.

observable standards, may reduce perceived discrimination.[25] Regardless of the cause, this heterogeneity is important as it suggests that firm level policies on performance pay will elicit a different response from non-white men.

As an additional subsample test, we consider whether any single form of performance pay drives our results. As mentioned, we do not know who receives group or individual performance pay. Similarly, we do not know if the performance standard is objective or subjective (the view of a supervisor). Thus, we first removed everyone who received a bonus. We then replaced those workers and removed everyone who received commissions and so on. While magnitudes varied modestly, the general pattern remains using any four of the types of performance pay. At minimum, this suggests no one form is driving the results.[26] A superior data source would be needed to distinguish the effects of individual and group schemes.

6.3 The Role of Depression

While we emphasize stress, home-work conflict and exhaustion, Dahl and Pierce (2019) find a tight connection between performance pay and antidepressant prescriptions. We have no information on prescriptions but have self-reports of moods experienced in the last month. These self-reports are available for five waves (2002, 2004, 2006, 2008 and 2010) and so reduce the sample substantially. These moods may be inherent personality characteristics not fundamentally tied to performance pay. Yet, Curme and Stefanec (2007) confirm that those on performance pay have substantially less "fatalism" and substantially greater "self-esteem." Green and Heywood (2008) argue that performance pay, after adjusting for sorting across individuals and jobs, tends to

[25]See Heywood and O'Halloran (2005) and Heywood and Parent (2012) for evidence on the extent to which performance pay reduces observed racial earnings gaps.
[26] These results are available upon request.

increase job satisfaction. Thus, at minimum it remains an open question what role a depressed mood plays in the relationship between performance pay and substance use.

We develop a composite index based on three questions. These asked "how often in the past month have you... "been a very nervous person"..."felt downhearted and blue"..."felt so down in the dumps that nothing could cheer you up"?" To each question the respondent answered: 1 = none of the time, 2 = some of the time, 3 = most of the time, and 4 = all of the time. As a first test we weighted all three questions equally and simply added the scores so that the response varied from 4 to 12. Alternatively, we simply entered the three separate mood variables. We then repeated our series of pooled and fixed-effect estimates.

Table 6 shows the results. First, the composite "depressive mood" indicator has a large and significantly positive association with substance use of all three types. Yet, the strong and robust roles for performance pay remains. For example, those on performance pay are 31 percent more likely to use marijuana, a figure that is unchanged by the addition of the mood indicator. It is also unchanged by breaking the three indicators into separate variables as shown in the second panel of Table 6. This is true even as each separate mood indicators takes a significant coefficient.

INSERT TABLE 6

The substantial and significant role for performance pay remains in the fixed-effect logits in Table 6. It does, however, follow the earlier pattern of being attenuated in size. In the match specific fixed effect estimates, the size remains (if not increasing) but the significance is lost. Yet, this is true not only for performance pay but for some of the mood indicators. This suggests a lack of precision due to the smaller sample size associated with using the mood variables available in only selected waves.

Our tentative conclusion is that deep-seated depression does not drive the association we identify. Individuals reporting depression more likely use substances but that does not generate the performance pay result. Thus, we continue to suggest that it may be exhaustion, uncertainty, stress and work-family conflict associated with performance pay that drives substance use.

7. Conclusions

Performance pay can align the interests of workers and their firms. This can improve profits to the firm and earnings to the worker. Yet, performance pay can also create unintended negative consequences. These unintended consequences are particularly important when they impact those outside the employment relationship. Substance use generates such externalities.

Performance pay creates incentives to exert effort, minimize breaks, take risks and work longer. It also inherently generates earnings uncertainty borne by the worker. This stress, exhaustion and uncertainty may lead to the coping behavior of substance use. Thus, we test the hypothesis that performance pay should be associated with substance use.

This hypothesis receives support in our pooled data from the NLSY. Proxies for ability, risk and personality do not eliminate the association while worker fixed effect models also confirm the association. Two employer-employee match fixed effect models also confirm the association. Finally, a fixed effect IV model continues to confirm the association. While accounting for sorting reduces the size of the association, it remains.

Subsample tests suggest remarkable persistence to the association. The exception is non-white males for whom the results are attenuated or even absent. This clearly remains an area for further research: both to confirm the heterogeneity in other data sources and to explain its cause. Also, in a data source with better household data it would be interesting to examine if performance pay

influences substance use of spouses or other family members. Such spillovers might be expected but our data do not allow an examination.

Our experiments with self-reported depressive moods showed that they were clearly associated with increased substance use. Yet, the role of performance pay was essentially unaltered by including the mood indicators. Future work using data on stress indicators, either self-reported or cortisol based, might see if their inclusion causes the role of performance pay to vanish.

We reiterate in closing that performance pay may still benefit workers, firms and society. We suggest only that any balancing of benefit and harm should likely include the elevated use of alcohol and illicit drugs. We recognize that even this elevation may make for complicated welfare judgements. Thus, Bray (2005) shows that moderate alcohol use does not reduce returns to education and Ullman (2014) argues that absences due to sickness declined following the legalization of medical marijuana in several US states. Yet, the overall consequences of substance use are associated with enormous societal costs and those costs, like those associated with the risk of injuries and health deterioration should be kept in mind when evaluating performance pay.

The authors declare that they have no conflict of interest.

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Table 1: Performance Pay and the Incidence of Drug and Alcohol Use, Pooled Cross-section Logit Estimates

	Marijuana	Hard drugs	Alcohol
Performance pay	0.035***	0.015***	0.072***
	(6.288)	(4.999)	(11.259)
	{1.287}	{1.351}	{1.449}
Female	-0.057***	-0.010**	-0.0458***
	(-7.283)	(-2.496)	(-5.543)
Black	-0.019**	-0.071***	-0.146***
	(-2.128)	(-10.664)	(-17.582)
Hispanic	-0.047***	-0.019***	-0.056***
	(-4.674)	(-3.562)	(-5.945)
Age	-0.005**	-0.002	0.005**
	(-2.176)	(-1.260)	(2.084)
Married	-0.131***	-0.049***	-0.112***
	(-14.704)	(-9.112)	(-14.408)
Education	-0.006***	-0.001	0.027***
	(-4.090)	(-1.563)	(17.272)
Hours	-4.5×10^{-4}**	-1.2×10^{-4}	9.1×10^{-4}***
	(-2.549)	(-1.184)	(3.968)
Health insurance	-0.043***	-0.015***	0.010*
	(-8.419)	(-5.588)	(1.699)
Constant	{1.118}	{0.229**}	{0.239***}
	(0.251)	(-2.109)	(-4.102)
Observations (person- years)	62,425	61,673	62,425
Number of people	8,383	8,359	8,383

Notes: Average marginal effects are reported with odds ratios in brackets, and t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18), region (4) and year/wave (10) fixed effects. Survey weights and estimation are used throughout, and heteroskedasticity robust standard errors are clustered at the individual level.

Table 2: Performance Pay and the Incidence of Drug and Alcohol Use: Controlling for Ability and Risk Attitudes in Pooled Cross-section Logit Estimates

	Marijuana	Hard drugs	Alcohol
Performance pay	0.033***	0.011***	0.065***
	(5.206)	(3.375)	(8.796)
	{1.274}	{1.265}	{1.413}
Hours	-3.2×10^{-4}	-4.6×10^{-5}	0.001***
	(-1.579)	(-0.412)	(4.280)
Log hourly wages	-0.001	-0.005**	0.039***
	(-0.245)	(-2.082)	(7.705)
ASVAB	0.041***	0.018***	0.058***
	(8.274)	(7.055)	(10.841)
Risk	0.024***	0.011***	0.023***
	(5.543)	(4.685)	(5.308)
Constant	{1.128}	{0.233*}	{0.228***}
	(0.231)	(-1.850)	(-3.548)
Observations (person-years)	46927	46475	46927
Number of people	5,870	5,864	5,870

Notes: Average marginal effects are reported with odds ratios in brackets, and t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Controls for Female, Black, Hispanic, Age, Married, Education and Health insurance are included but not reported. All specifications include occupation (19), industry (18), region (4) and year/wave (10) fixed effects. Survey weights and estimation are used throughout, and heteroskedasticity robust standard errors are clustered at the individual level.

Table 3: Performance Pay and Drug and Alcohol Use, Worker and Worker-Employer Match Fixed Effects

	Worker Fixed Effects			Worker in Employer Fixed Effects		
	Marijuana	Hard drugs	Alcohol	Marijuana	Hard drugs	Alcohol
Performance pay	1.158***	1.207**	1.122***	1.290***	1.258*	1.134**
	(3.123)	(2.573)	(3.049)	(3.260)	(1.810)	(2.071)
Age	0.933	1.037	0.983	0.982	0.953	1.101
	(-1.064)	(0.322)	(-0.334)	(-0.170)	(-0.282)	(1.317)
Married	0.582***	0.519***	0.661***	0.673***	0.614**	0.697***
	(-6.841)	(-4.901)	(-8.064)	(-2.792)	(-2.221)	(-4.549)
Education	0.988	0.976	1.098***	0.990	0.971	1.003
	(-0.639)	(-0.833)	(6.832)	(-0.289)	(-0.667)	(0.137)
Hours	0.998	1.005*	1.005***	1.001	1.012*	1.001
	(-0.992)	(1.901)	(3.707)	(0.182)	(1.797)	(0.586)
Health insurance	0.833***	0.900	0.841***	0.734***	0.999	0.780***
	(-4.047)	(-1.536)	(-4.986)	(-3.919)	(-0.008)	(-4.372)
Log hourly wages	1.015	1.005	1.108***	1.025	0.941	1.058
	(0.464)	(0.100)	(3.957)	(0.425)	(-0.593)	(1.145)
Obs. (person-years)	22,442	9,947	38,976	8,140	3,411	16,809
Number of people	2,829	1,247	4,925			
Num. person-emp.				2,207	917	4,304

Notes: Odds ratios are reported, with t-statistics in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18), region (4) and year/wave (10) fixed effects. Heteroskedasticity robust standard errors are clustered at the worker level in the first three columns and at the worker-employer match level in the last three columns.

Table 4: FE-IV Estimates of Substance Use

	Worker Fixed Effects OLS		
	Marijuana	**Hard drugs**	**Alcohol**
	Second-stage results		
Performance Pay	0.032**	0.027***	0.044**
	(2.033)	(3.590)	(2.056)
Age	0.001	-6.14×10^{-4}	0.002
	(0.160)	(-0.022)	(0.275)
Married	-0.021***	-0.009***	-0.048***
	(-4.740)	(-3.097)	(-7.990)
Education	-0.002*	-0.002**	0.006***
	(-1.769)	(-1.998)	(3.709)
Hours	-9.48×10^{-5}	1.62×10^{-4}**	4.28×10^{-4}***
	(-0.820)	(2.090)	(2.654)
Health insurance	-0.013***	-0.004*	-0.020***
	(-3.843)	(-1.824)	(-4.299)
Log wages	0.005*	0.001	0.013***
	(1.936)	(0.519)	(3.825)
	First-stage results		
Instrument	0.497***	0.499***	0.497***
	(48.850)	(48.700)	(48.850)
Cragg-Donald Wald F	2386.61	2371.78	2386.61
Durbin-Wu-Hausman chi-sq	2.628	9.437***	2.271
Observations	54500	53820	54500

Notes: The identifying instrument in the first stage is the lagged value of the proportion of the worker's three-digit occupation that receives performance pay. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include industry (18), region (4) and year/wave (9) fixed effects. Survey weights and estimation are used.

Table 5: Performance Pay and Substance Use, Heterogeneous Effects

	Marijuana			
	White		Nonwhite	
	Women	Men	Women	Men
Performance pay	0.037***	0.040***	0.032**	-0.007
	(3.715)	(3.545)	(2.304)	(-0.474)
	{1.373}	{1.297}	{1.364}	{0.954}
Marijuana proportion	0.149	0.211	0.112	0.188
Performance pay proportion	0.238	0.217	0.188	0.198
Observations (person-years)	12,633	13,447	11,003	9,824

	Hard drugs			
	White		Nonwhite	
	Women	Men	Women	Men
Performance pay	0.014**	0.015**	0.011	-0.006
	(2.428)	(2.513)	(1.408)	(-0.908)
	{1.337}	{1.288}	{1.531}	{0.842}
Hard drugs proportion	0.053	0.066	0.023	0.038
Performance pay proportion	0.239	0.218	0.188	0.199
Observations (person-years)	12,482	13,321	10,748	9,598

	Alcohol			
	White		Nonwhite	
	Women	Men	Women	Men
Performance pay	0.082***	0.051***	0.080***	0.034**
	(6.339)	(3.998)	(4.678)	(2.013)
	{1.575}	{1.337}	{1.438}	{1.175}
Alcohol proportion	0.724	0.756	0.550	0.625
Performance pay proportion	0.238	0.217	0.188	0.198
Observations (person-years)	12,633	13,447	11,023	9,824

Notes: Average marginal effects are reported with odds ratios in brackets. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Survey weights and estimation are used throughout and heteroskedasticity robust standard errors are clustered at the individual level. Estimations include all Table 2 controls.

Table 6: Performance Pay and Substance Use: Controlling for Mood (Fixed Effects)

	Depression (aggregate)			Depression (individual)		
	Marijuana	Hard drugs	Alcohol	Marijuana	Hard drugs	Alcohol
Performance pay	1.307***	1.255***	1.371***	1.307***	1.259***	1.370***
	(-4.71)	(-2.647)	(-6.494)	(-4.713)	(-2.633)	(-6.501)
Depression	1.229***	1.344***	1.010***			
	(-13.40)	(-13.29)	(-6.911)			
Nervous				1.242***	1.287***	1.134***
				(-5.591)	(-4.302)	(-3.931)
Blue				1.322***	1.438***	1.144***
				(-7.051)**	(-5.567)	(-3.937)
In-the-dumps				1.114***	1.310***	1.016
				(-2.461)	(-4.229)	(-0.429)
Obs. (person-years)	22,906	22,741	22,906	22,906	22,741	22,906

Notes: These estimates include all of the covariates in Table 2. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18), region (4) and year/wave (10) fixed effects. Survey weights and estimation are used throughout and heteroskedasticity robust standard errors are clustered at the individual level.

Appendix Table A1: Descriptive statistics and variable definitions, NLSY97, 2002/2011

Variable definitions	Obs.	Mean	Std. Dev.
Marijuana = 1 if respondent used marijuana, or grass/pot, in the last 30 days and 0 otherwise	62425	0.168	0.374
Hard drugs = 1 if respondent, since the date of last interview, has used any drugs like cocaine, crack, heroin, or crystal meth, or any other substance not prescribed by a doctor, in order to get high or achieve an altered state and 0 otherwise	61673	0.046	0.210
Alcohol = 1 if respondent had one or more drinks of an alcoholic beverage in the last 30 days and 0 otherwise	62425	0.663	0.473
Marijuana frequency = number of days respondent has used marijuana in the last 30 days	61377	2.119	6.765
Hard drugs frequency = estimated number of times respondent has used hard drugs since the date of last interview	61595	1.849	22.468
Alcohol frequency = number of days respondent had one or more alcoholic beverages in the last 30 days	61777	4.695	6.489
Performance pay = 1 if respondent received extra compensation from tips, commissions, bonuses, incentive pay, or other	62425	0.211	0.408
Female = 1 if respondent is a female and 0 if otherwise	62425	0.497	0.500
Black = 1 if respondent is black and 0 otherwise	62425	0.252	0.434
Hispanic = 1 if respondent is hispanic and 0 otherwise	62425	0.214	0.410
Age = respondent's age in years	62425	24.336	3.151
Married = 1 if respondent is married and 0 otherwise	62425	0.221	0.415
Education = highest year of education attained	62425	13.159	2.475
Hours = usual weekly hours worked	62425	34.450	13.157
Health insurance = 1 if respondent has any kind of health care coverage	62425	0.674	0.469
Log hourly wages = natural log of base hourly wage rate	61438	2.398	0.671
ASVAB = Armed Services Vocational Aptitude Battery combined percentile ranking of respondents scores in mathematical knowledge, arithmetic reasoning and verbal. Extracted from the 1999 wave of the NLSY97.	50863	46.910	29.188
Risk = respondent's self-selected risk preference scale from 0 to 10 where 0 means "unwilling to take any risks" and 10 means "fully prepared to take risks". Extracted from the 2010 wave of the NLSY.	58058	5.596	2.533

Table A2: Performance Pay and the Incidence of Drug and Alcohol Use: Controlling for Ability, Risk Attitudes and Log Total Wages in Pooled Cross-section Logit Estimates

	Marijuana	**Hard drugs**	**Alcohol**
Performance pay	0.033***	0.012***	0.049***
	(5.121)	(3.606)	(6.661)
	{1.275}	{1.288}	{1.298}
Hours	-3.2×10^{-4}	-4.6×10^{-5}	0.001***
	(-1.575)	(-0.400)	(4.417)
Log total wage	-8.5×10^{-5}	-0.001	0.045***
	(-0.020)	(-0.513)	(8.548)
ASVAB	0.041***	0.018***	0.058***
	(8.267)	(7.058)	(10.761)
Risk	0.024***	0.011***	0.022***
	(5.541)	(4.685)	(5.223)
Constant	{1.117}	{0.233*}	{0.073***}
	(0.200)	(-1.709)	(-5.893)
Observations (person-years)	46927	46475	46927
Number of people	5,870	5,864	5,870

Notes: Average marginal effects are reported with odds ratios in brackets. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Controls for Female, Black, Hispanic, Age, Married, Education and Health insurance included but not reported. All specifications include occupation (19), industry (18), region (4) and year/wave (10) fixed effects. Log total wage is the natural log of the hourly wage rate including compensation from performance pay schemes. Survey weights and estimation are used throughout and heteroskedasticity robust standard errors are clustered at the individual level.

Table A3: Worker fixed effects Poisson estimations: frequency of use

	Marijuana	Hard drugs	Alcohol
	(1)	(2)	(3)
Performance pay	0.083***	0.197*	0.041***
	(3.095)	(1.956)	(3.230)
Age	-0.144***	0.255	-0.028
	(-3.512)	(1.444)	(-1.471)
Married	-0.249***	-0.595***	-0.154***
	(-4.497)	(-3.218)	(-7.470)
Education	-0.001	0.029	0.030***
	(-0.097)	(0.498)	(5.343)
Hours	-0.000	-0.000	0.002***
	(-0.417)	(-0.042)	(3.647)
Health insurance	-0.042	-0.144	-0.040***
	(-1.612)	(-1.278)	(-2.990)
Log hourly wages	0.032*	-0.063	0.017*
	(1.844)	(-0.905)	(1.751)
Obs. (person-years)	21,676	8,982	54,886

Notes: Heteroskedasticity robust standard errors are clustered at the individual level. Column (2) estimates exclude workers using hard drugs more often than every workday (407 observations). t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18), region (4) and year/wave (9) fixed effects.

Table A4: Poisson estimations: Number of Substances Used (zero to three)

	Number of Substances Used		
	Pooled cross-section	**Worker fixed effects**	**Worker in employer FE**
Performance pay	0.135***	0.036***	0.038***
	(12.268)	(4.992)	(3.966)
Age	-0.006	-0.008	0.007
	(-1.195)	(-0.728)	(0.560)
Married	-0.283***	-0.104***	-0.078***
	(-18.335)	(-8.917)	(-5.082)
Education	0.027***	0.011***	-0.001
	(8.696)	(3.681)	(-0.345)
Hours	0.001**	0.001***	0.001
	(1.965)	(2.675)	(1.461)
Health insurance	-0.061***	-0.040***	-0.053***
	(-5.123)	(-5.152)	(-4.796)
Log hourly wages	0.047***	0.018***	0.008
	(5.848)	(3.092)	(0.941)
Constant	-0.418***	-----	-----
	(-3.247)	-----	-----
Wald Chi-Squared	1196.0***	335.9***	151.4***
Observations	60719	55411	36789

Notes: The dependent variable is a count of the number of substances used by the respondent. Heteroskedasticity robust standard errors clustered at the individual level. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18), region (4) and year/wave (9) fixed effects.

Table A5: Examining other Lifestyle Indicators

	Pooled Logits			Worker Fixed Effects			Worker in employer FE		
	Pray	**Sex**	**Smoke**	**Pray**	**Sex**	**Smoke**	**Pray**	**Sex**	**Smoke**
Performance pay	-0.024***	0.035***	0.023***	0.992	1.040	1.034	1.115	0.983	1.080
	(-2.647)	(5.482)	(3.218)	(-0.115)	(1.193)	(0.720)	(0.667)	(-0.334)	(1.011)
	{0.888}	{1.174}	{1.119}						
Female	0.080***	0.056***	-0.002	-----	-----	-----	-----	-----	-----
	(7.893)	(7.305)	(-0.156)	-----	-----	-----	-----	-----	-----
Black	0.235***	-0.045***	-0.168***	-----	-----	-----	-----	-----	-----
	(24.275)	(-5.153)	(-14.365)	-----	-----	-----	-----	-----	-----
Hispanic	0.058***	-0.028***	-0.137***	-----	-----	-----	-----	-----	-----
	(4.953)	(-2.893)	(-10.844)	-----	-----	-----	-----	-----	-----
Age	0.002	0.004*	0.018***	1.084	0.883***	0.587**	1.064	0.910	0.936
	(0.668)	(1.772)	(5.584)	(0.852)	(-2.734)	(-2.446)	(0.264)	(-1.497)	(-0.704)
Married	0.106***	0.270***	-0.123***	1.309***	2.519***	0.582***	1.058	2.209***	0.646***
	(11.048)	(33.257)	(-12.690)	(3.280)	(17.811)	(-7.920)	(0.328)	(10.186)	(-3.976)
Education	-0.007***	1.82×10^{-4}	-0.044***	0.932***	1.118***	0.971*	0.973	1.042**	0.977
	(-3.290)	(0.116)	(-22.839)	(-2.750)	(8.726)	(-1.648)	(-0.462)	(1.993)	(-0.809)
Hours	-0.001***	0.002***	0.001***	0.994***	1.003***	1.002	0.998	1.001	1.005
	(-3.517)	(7.553)	(4.307)	(-2.639)	(3.070)	(1.492)	(-0.329)	(0.350)	(1.560)
Health insurance	0.018**	0.008	-0.079***	0.936	1.025	0.854***	0.830	1.093*	0.908
	(2.169)	(1.317)	(-11.794)	(-1.009)	(0.791)	(-3.501)	(-1.029)	(1.813)	(-1.277)
Log hourly wages	-0.028***	0.042***	-0.010*	0.864***	1.119***	0.993	0.889	1.048	0.999
	(-4.461)	(8.668)	(-1.956)	(-2.987)	(4.986)	(-0.225)	(-0.734)	(1.120)	(-0.018)
Years / waves (10)	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Years / waves (4)	Yes	No	No	Yes	No	No	Yes	No	No
Observations	23,715	61,438	61,438	7,849	47,314	25,059	1,769	21,180	10,122

Note: Average marginal effects reported in the Logit estimations with odds ratios in brackets; odds ratios are reported in the fixed effects estimations. Heteroskedasticity robust standard errors clustered at the individual level. t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All specifications include occupation (19), industry (18) and region (4) fixed effects in addition to year/wave fixed effects as indicated.

Table A6: FE OLS Estimates of Substance use

	Worker Fixed Effects OLS		
	Marijuana	**Hard drugs**	**Alcohol**
Performance Pay	0.011***	0.007***	0.016***
	(3.266)	(3.026)	(3.484)
Age	-0.004	-0.001	-0.001
	(-0.808)	(-0.356)	(-0.226)
Married	-0.024***	-0.010***	-0.053***
	(-5.724)	(-3.507)	(-9.240)
Education	-3.02×10^{-4}	-3.0×10^{-4}	0.010***
	(-0.257)	(-0.389)	(6.542)
Hours	-7.55×10^{-5}	1.92×10^{-4}***	4.78×10^{-4}***
	(-0.680)	(2.629)	(3.199)
Health insurance	-0.013***	-0.003	-0.023***
	(-3.947)	(-1.504)	(-5.426)
Log wages	0.003	0.001	0.012***
	(1.222)	(0.396)	(3.724)
Years / waves (9)	Yes	Yes	Yes
Constant	0.258*	0.057	0.546***
	(1.897)	(0.632)	(2.990)
Observations	61,299	60,582	61,299

Notes: t-statistics are in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Survey weights and estimation are used. All specifications include occupation (19), industry (18) and region (4) fixed effects in addition to year/wave fixed effects indicated.