Extended abstract for
The effect of seasonal unemployment on drug use[*]

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Drug abuse costs the US more than $740 billion annually, with more than 70,000 overdose deaths every year (National Institute of Drug Abuse [NIDA], 2017; NIDA, 2019). Despite the high addiction disease burden, we have little causal evidence on factors that lead to illicit drug use. In particular, while many papers have studied the impact of economic conditions on legal substances like alcohol and tobacco use (see Pacula, 2011, and Henkel, 2011, for reviews), few have studied illicit drugs, and only one study (Carpenter, McClellan, & Rees, 2017) has systematically investigated all categories of illicit drugs.[1]

In this paper, we estimate the effect of unemployment on drug use in the 2004 to 2014 National Survey on Drug Use and Health (NSDUH), the largest drug-use survey in the US on which most official statistics are based. To identify a causal effect, we restrict attention to one particular type of unemployment frequently ignored by economists: seasonal unemployment. Seasonal unemployment is generated when demand for labor falls according to the time of the year, and is generally driven by factors unrelated to individual worker preferences. Because drivers of seasonality in macroeconomic conditions (weather, holidays, etc.) are not relevant in explaining aggregate trends, economists tend to treat it as a nuisance variable. Yet, it is precisely this irrelevance towards the current economy that makes seasonality plausibly exogenous. In addition, employment seasonality varies appreciably across industries and occupations. In this paper, we exploit this difference in seasonality across industries and occupations using a difference-in-differences strategy to estimate the effect of unemployment on drug use.

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[1] Other papers have focused on specific drugs like marijuana (Arkes, 2007; Arkes, 2011; Pabilonia, 2017) and opioids (Currie, Jin, & Schnell, 2019).

We illustrate the variation used in this paper in Figure 1, which shows the monthly US employment rate (employment-to-population ratio) between 1976 and 2018. While macroeconomic trends between years drive much of the variation, intra-year seasonal variation is still evident, and accounts for 6 percent of the time series variation.[2] Figure 2 shows that this seasonality varies appreciably across industries; the July-January employment rate ratio—generally the highest and lowest months of employment respectively—ranges from 1.4 in the entertainment industry to 1.005 in durable manufacturing.

To estimate the effect of seasonal non-employment on drug use, we match individuals in the NSDUH to a measure of seasonality that they experience based on the quarter of interview, as well as the industry and occupation they work in, available as long as the individual worked within the past year.[3] We estimate the two-stage least squares (2SLS) specification

$$y_{icyq} = \beta NonEmployed_{icyq} + \psi_{cy} + \zeta_{yq} + \varepsilon_{icyq}, \tag{1a}$$

$$NonEmployed_{icyq} = \tilde{\beta} \log\left(SeasEmp_{cyq}\right) + \tilde{\psi}_{cy} + \tilde{\zeta}_{yq} + \nu_{icyq}, \tag{1b}$$

where y_{icyq} is an indicator variable equal to one if person i working in industry-occupation cell c in year y and quarter q used a drug, and $NonEmployed_{icyq}$ is an indicator variable equal to one if the person is not working. $SeasEmp_{cyq}$ is the cell's average leave-one-out employment rate (employment as a percentage of the national population) for the calendar quarter, constructed using the Current Population Survey (CPS) between 1984 and 2018:[4]

[2] The variance decomposition is implemented using Stata's xtreg procedure, and is based on the law of total variance.

[3] Interviews in the NSDUH are monthly, and we use questions for the month prior to the interview. The reference quarters are hence December to February, March to May, June to August, and September to November.

[4] We use the Integrated Public Use Microdata Series (IPUMS) database (Flood, King, Rodgers, Ruggles, & Warren, 2018).

$$SeasEmp_{cyq} = \sum_{\substack{y=1984 \\ y \neq y}}^{2014} \frac{Emp_{cyq}}{Pop_y} \times 100\% \tag{2}$$

where Emp_{cyq} is the total employment of cell c in year y and calendar quarter q, and Pop_y is the national population for that year.[5] The main coefficient of interest is β: the effect of non-employment on substance use. We cluster standard errors by industry-occupation cells. Industry-occupation-year fixed effects (ψ_{cy} and $\tilde{\psi}_{cy}$) ensure that we compare individuals working in the same industry, occupation and year, while year-quarter fixed effects (ζ_{yq} and $\tilde{\zeta}_{yq}$) protect against spurious correlation due to factors like the weather. In this specification, the main identifying assumption required is that individuals in different industries and occupations respond similarly to seasonal employment.

Table 1 shows our main results based on public-use data: the effect of seasonal non-employment on drug use.[6] In column 1, we report the effect on any illicit drug use. On average, non-employment increases the probability of use of any illicit drug by 5 percentage points. The next six columns report the effect on major drug categories. All point estimates are positive, but only the effects on opioids (heroin and painkillers) and depressants (tranquilizers and sedatives, for example, sleeping pills) use are statistically significant, both at 3 percentage points. In contrast with earlier papers investigating alcohol, we do not find that seasonal non-employment affects alcohol or tobacco use (columns 8 and 9).[7]

The estimates we obtain must be interpreted in context of the source of variation that we use. Non-employment is thought to affect substance use through three main channels. First, there is an income effect associated with job loss; papers that find a negative effect of unemployment on

[5] To improve precision, we exclude observations when $SeasEmp_{cyq}$ is computed based on less than 500 individuals in the microdata.

[6] The coefficient on the first stage is 0.4: on average, as aggregate seasonal employment increases by 1 percent—the denominator of the employment rate can be ignored because there is no seasonality in population—individuals in the NSDUH become 0.4 percent less likely to be working.

[7] The 2SLS specification means that our estimates are comparable with studies that investigate the effect of unemployment on drug use at the individual level. To compare with studies based on macroeconomic conditions, we can obtain approximations of reduced form estimates by multiplying by the first stage coefficient of 0.4. However, note that these reduced form estimates are still not exactly comparable, since we do not have measures of industry-occupation level *unemployment rates*.

alcohol (a procyclical effect) generally conclude that this dominates during recessions. The second channel, emphasized by Case & Deaton (2017) among others, is the psychological channel, which leads to increased drug use and "deaths of despair". Because of the nature of seasonal non-employment—highly predictable and short-lived—these two factors are minimized in our setting: individuals should be smoothing savings across good and bad employment months, and there should be little psychological stress if one expects employment prospects to improve in a few months. Instead, our results are likely to be driven by a third channel frequently ignored in the literature: increases in time availability in months of low employment demand. This suggests that a simple addiction policy response might be to encourage or provide other (healthier) leisure activities that target the unemployed.

In further work, we are awaiting access to restricted-use data to verify the above estimates using finer sectors and timing. Restricted-use data also provides access to geographic variables: this provides a further test of our hypothesis, and also allows us to better contrast with results from other studies using general unemployment.

References

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Figure 1: Monthly employment rate, 1976 to 2018

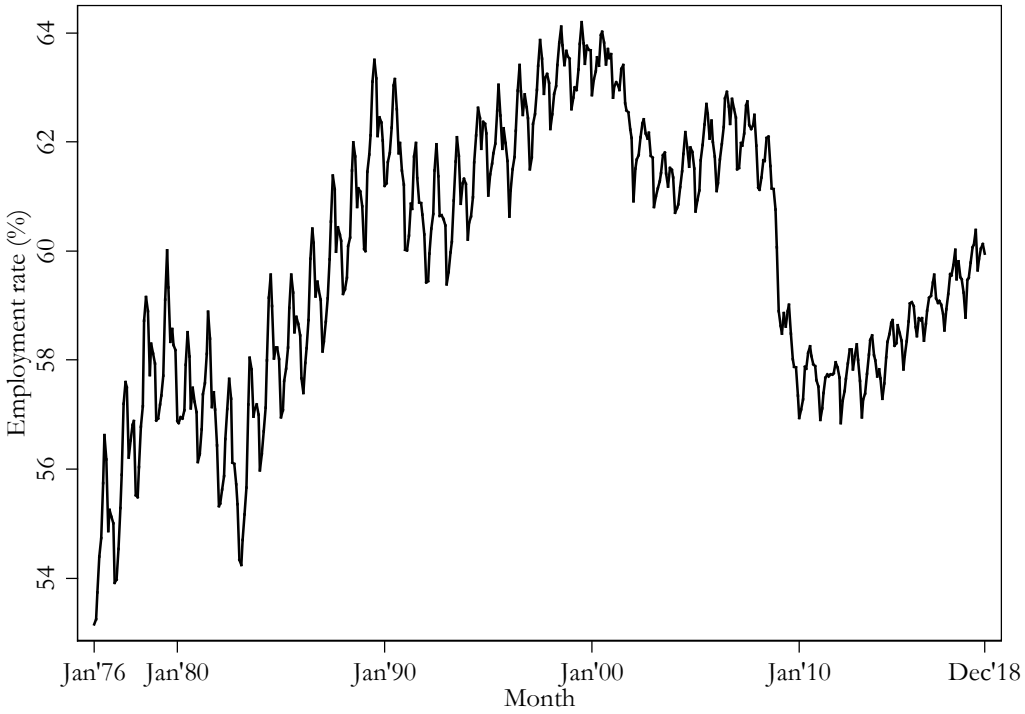
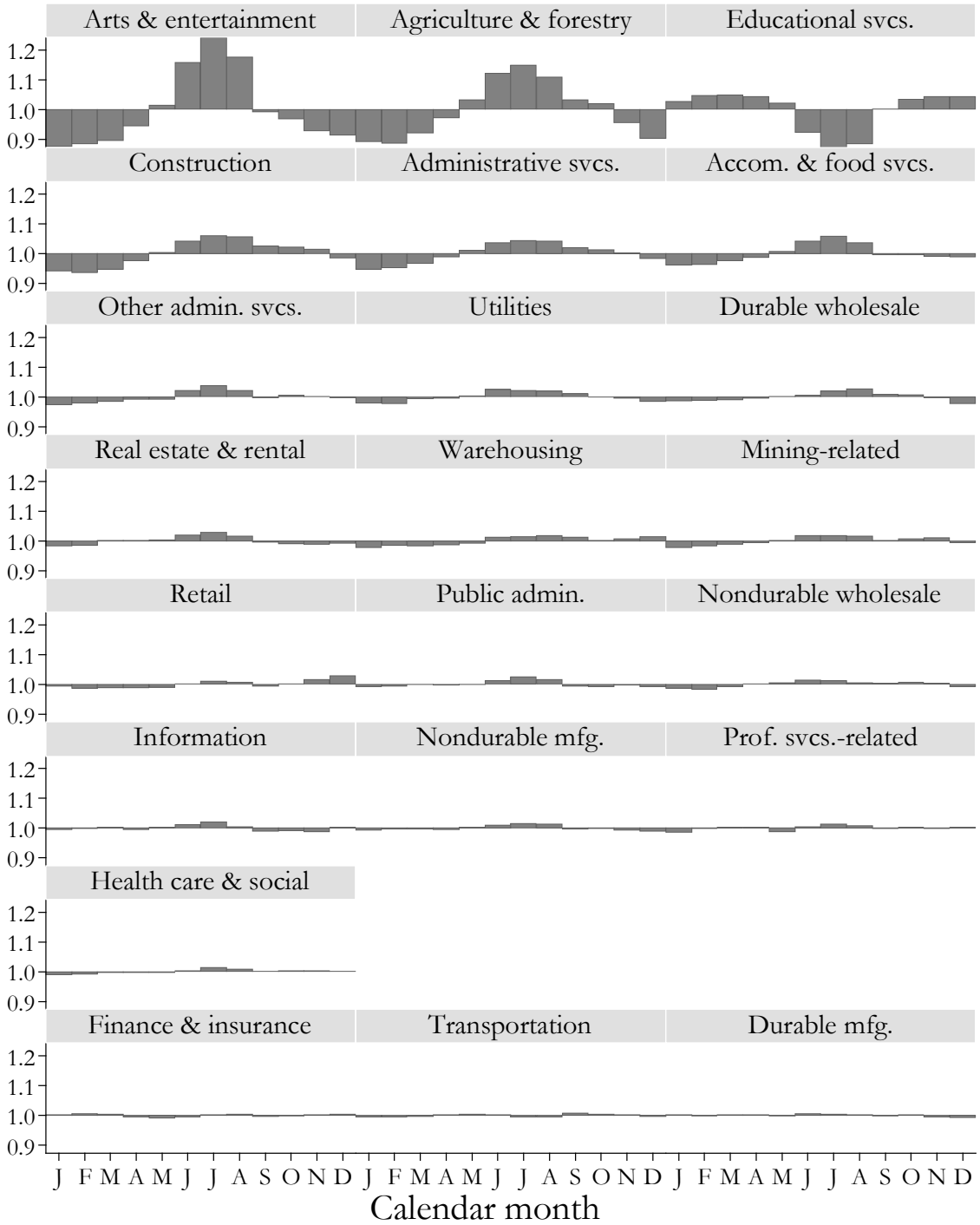


Figure 2: Employment rate of each calendar month relative to industry average



Notes: Each sub-figure shows the calendar month's employment rate relative to the average over all calendar months for the specified industry between 1976 and 2018.

Table 1: Effect of seasonal unemployment on substance use

	Dependent variable: Use/abuse of the specified substance in past month:								
	Any illicit drug	Marijuana	Opioids	Stimulants	Depressants	Hallucin-ogens	Inhalants	Alcohol	Tobacco
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-employed	0.052**	0.023	0.028**	0.018	0.026**	0.018*	0.0053	-0.039	0.038
	(0.020)	(0.023)	(0.013)	(0.012)	(0.011)	(0.011)	(0.0050)	(0.044)	(0.043)
Observations	372,564	372,564	372,564	372,564	372,564	372,564	372,564	372,564	372,564
No. of industry-occupation cells	206	206	206	206	206	206	206	206	206
Proportion using drug	0.15	0.13	0.032	0.019	0.013	0.010	0.0033	0.59	0.37
First stage F-statistic	414	414	414	414	414	414	414	414	414

Notes: Standard errors clustered by industry-occupation cells in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises non-institutionalized civilians in the 2004 to 2014 NSDUH who ever worked in the past year. The dependent variables are indicator variables equal to one if the person abused a drug in the specified category in the month prior to the interview. Illicit drugs are marijuana, opioids, stimulants, depressants, hallucinogens, and inhalants. Non-employed is an indicator variable equal to one if the person did not work in the month prior to the interview. The instrument used is the log of the seasonal employment rate of the industry-occupation cell, see text for details. The observation is omitted if the seasonal employment rate is computed based on fewer than 500 individuals in the microdata. All columns include as controls industry-occupation-year fixed effects and year-quarter fixed effects.