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RECESSIONS AND ADMISSIONS TO SUBSTANCE ABUSE TREATMENT

Jonathan H. Cantor
Brady P. Horn
Johanna Catherine Maclean

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ABSTRACT

Previous economic research shows that recessions lead to worsening substance abuse. In this paper we study the effect of recessions on admissions to specialty substance abuse treatment using administrative data between 1992 and 2015. Using data from Treatment Episode Data Set and a differences-in-differences empirical strategy, we find no evidence that recessions influence the overall number of admissions. However, we document substantial heterogeneity across drugs of abuse. Combining our findings with previous economic studies suggests that unmet need for substance abuse treatment increases during recessions.

Jonathan H. Cantor
RAND Corporation
1776 Main Street
Santa Monica, CA 90401
jcantor@rand.org

Brady P. Horn
Department of Economics University
of New Mexico
Econ 2023B, Albuquerque, NM 87131
bhorn@unm.edu

Johanna Catherine Maclean
Department of Economics
Temple University
Ritter Annex 869
Philadelphia, PA 19122
and NBER
catherine.maclean@temple.edu

1. Introduction

There is a complex relationship between economic recessions and health. *Ceteris paribus*, recessions decrease income and, according to standard health economic theory (Grossman 1972), reductions in income worsen health by decreasing resources available for health investments. However, in his seminal work, Ruhm (2003, 2000, 2005, 2008, 1995) documented a somewhat controversial finding: recessions *improve* a wide range of health and health behaviors. Ruhm outlined a series of economic mechanisms through which recessions may influence health and health behaviors. First, during recessions workers are more likely to lose their job, which lowers their opportunity cost of time. Thus, the full cost of time-intensive health investments (e.g., physical activity) declines and, all else equal, these investments should increase during recessions. Second, if health is a normal good – which canonical health economic models assume, e.g., Grossman (1972) – health demand will decline in recessions as income levels fall. Third, during recessions individuals also tend to lose health insurance, which increases the out-of-pocket price of healthcare services which should lead to a reduction in the quantity of healthcare services demanded and thus worsen health. Fourth, during expansions, the employed work longer hours and are more likely to experience on-the-job injuries and strain, which should reduce health. Fifth, immigration to areas experiencing growth creates congestion and the emergence/spread of communicable diseases leading to worse health.

The mechanisms outlined by Ruhm operate in opposition to one another, with income and insurance effects implying that recessions should worsen health and other mechanisms implying that recessions should improve health. Thus, the overall effect of recessions on health *ex ante* ambiguous and empirical study is required.[1] Moreover, it is plausible that the overall

[1]Ruhm showed that the vast majority of health outcomes and health behaviors improve during recessions, suggesting that reductions in prices for time-intensive health investments, job-related health impairments, and immigration-

effect of recession varies across health outcomes.[2] In this study, we extend the economic literature on recessions and health, and address the following question: What is the effect of recessions on admissions to specialty substance abuse treatment?

Substance abuse is an important health outcome potentially influenced by recessions (Ruhm 1995) and is prevalent in the U.S. For instance, 22 million individuals 12 years and older, or 8.5% of the population, met diagnostic criteria for substance abuse in 2015 (Center for Behavioral Health Statistics and Quality 2015). These conditions impede health, employment, and relationships of afflicted individuals. Substance abuse is one of the leading causes of preventable death in the U.S. Such deaths exceed suicides, traffic fatalities, and firearm-related deaths (Murphy, Xu, and Kochanek 2013). Recent estimates suggest that, by 2020, the costs of substance abuse treatment within the U.S. will be $42B per year, with the vast majority ($30B or 71%) of this treatment financed by public payers (Substance Abuse and Mental Health Services Administration 2014). In terms of other important economic outcomes, substance abuse has been linked with increased general healthcare use and costs (Balsa et al. 2009; Mark et al. 2016), crime and violence (Carpenter 2007; French and Maclean 2006; Markowitz 2000), and reduced labor market productivity (Terza 2002). Estimates suggest that the economic cost of substance abuse to the U.S. is $519B per year (Caulkins, Kasunic, and Lee 2014).[3] Moreover, there is convincing economic evidence that substance abuse, for a wide range of substances including

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related congestion and disease-incidence offset reductions in income and increases in healthcare service prices faced by consumers. One exception is mental health, which appears to decline during recessions. Ruhm also advanced the literature substantially in terms of highlighting methodological limitations in previous, primarily non-economic, studies. For example, Ruhm noted that many studies did not account for area-level unobservable heterogeneity and failure to account for this heterogeneity lead to substantial bias in regression coefficient estimates.

[2] Indeed, the literature has produced a mixed set of estimates, suggesting that effects vary across health outcomes.

[3] This estimate is inflated by the authors from the original estimate of $481B (with $255B attributable to alcohol and $226B attributable to illicit drugs) in 2011 dollars to 2017 dollars using the Consumer Price Index.

alcohol and opioids, increases during recessions (Davalos, Fang, and French 2012; Frijters et al. 2013; Carpenter, McClellan, and Rees 2017; Hollingsworth, Ruhm, and Simon 2017).[4]

To mitigate the substantial internal and external costs associated with substance use there are numerous effective and cost-effective treatment options available (Swensen 2015; Kresina and Lubran 2011; Popovici and French 2013; Lu and McGuire 2002; French and Drummond 2005; Cartwright 2000; McCollister and French 2003; Schori 2011), including treatments for opioid abuse (Murphy and Polsky 2016; Volkow et al. 2014; Doran 2008). Although the effectiveness and cost-effectiveness of substance abuse treatment is well-established, most individuals who would benefit from such treatment do not receive it. For instance, recent work shows that, among individuals predicted to suffer from substance abuse, 7% receive treatment (Creedon and Cook 2016). While there are myriad reasons for failure to receive treatment, inability to pay is an important barrier (Center for Behavioral Health Statistics and Quality 2016). As financial resources available for all goods, including healthcare services, decline and individuals lose health insurance (Simon, Soni, and Cawley 2017; Cawley and Simon 2005) during recessions, cost barriers to treatment may increase. However, there is no economic evidence on how substance abuse treatment utilization varies across the U.S. business cycle.

Factors outside those advanced by Ruhm may be relevant for substance abuse and may also be influenced by recessions. Financial strain, which is likely more prevalent during recessions than other periods of the business cycle as income levels fall and poverty rates rise (Hoynes, Miller, and Schaller 2012), leads to worse mental health (Maclean et al. 2015; Maclean, Webber, and French 2015). Mental health is the one health outcome that Ruhm, and

[4] We note that the relationship between recessions and more moderate measures of substance use (e.g., any use, binge drinking, and heavy drinking) is mixed. However, as we argue later in the manuscript, these forms of substance use are less relevant for our research question which relates to serious substance abuse problems.

others, consistently show declines during recessions (Ruhm 2000; Charles and DeCicca 2008; Tefft 2011; Bradford and Lastrapes 2013; Davalos and French 2011). Individuals may self-medicate financial strain-induced mental health problems with substances, leading to substance abuse and, in turn, treatment (Khantzian 1997; Peirce et al. 1994). Moreover, a substantial share of substance abuse treatment is provided by government for free, or at a heavy discount, to patients. Such provision of care may mute cost-based barriers to treatment but may leave patients who rely on government-financed treatment vulnerable to state budgets which contract during recessions (Substance Abuse and Mental Health Services Administration 2014). Finally, the substance abuse treatment delivery system operates at capacity with limited financial resources available to absorb increases in demand that may occur during recessions and/or reductions in government funding (Carr et al. 2008; Buck 2011).

In this study, we examine how admissions to specialty substance abuse treatment vary across the U.S. business cycle. Specialty care is defined as a hospital, a residential facility, an outpatient treatment facility, or other facility with a treatment program that offers substance abuse treatment. To study the relationship between recessions and specialty substance abuse treatment utilization, we use administrative data from the Treatment Episodes Data Set (TEDS) between 1992 and 2015. We estimate differences-in-differences models that control for a wide range of state characteristics and state-specific linear trends. Also, we test for heterogeneity across substances of abuse, in particular opioids; both heroin and prescription opioids given that the U.S. is in the midst of the largest opioid epidemic in the history of the country (U. S. Department of Health and Human Services 2017).

We find no evidence that recessions influence the overall number of admissions to specialty substance abuse treatment. However, we identify heterogeneity across substances of abuse. More specifically, a one percentage point increase in the state unemployment rate leads to an 8.5% reduction in heroin admissions, a 7.0% increase in stimulant admissions, and a 6.9% increase in admissions for drugs not classified elsewhere. Combining these findings with previous economic studies showing that substance abuse worsens in recessions suggests that unmet need for substance abuse treatment increases during recessions. Put differently, substance abuse worsens during recessions, but there is no commensurate increase in specialty treatment for most substances. Thus, many individuals with serious substance abuse problems are plausibly remaining untreated during recessions.

While obviously recessions create government budget shortages, and numerous social programs must be constrained (Association of Schools of Public Health 2008; Gordon 2012), unmet need for substance abuse treatment can be extraordinarily costly to society. Thus, although recessions require difficult funding allocation decisions, policymakers may wish to prioritize substance abuse treatment, given the social costs associated with this health condition and the benefits from treatment for both patients and society at large.

The remainder of the paper proceeds as follows. Section 2 provides background on substance abuse and substance abuse treatment, and a review of the related literature. Our data, variables, and methods are reported in Section 3. Section 4 outlines the main findings and robustness checking is reported in Section 5. Finally, Section 6 concludes.

2. Background and related literature

2.1 Background on substance abuse treatment

Substance abuse 'occurs when the recurrent use of alcohol and/or drugs causes clinically and functionally significant impairment, such as health problems, disability, and failure to meet major responsibilities at work, school, or home' according to the Substance Abuse and Mental

Health Service Administration (SAMHSA) (2015). Diagnosis of substance abuse[5] is established using information on diminished control, social impairment, use of substances, and so forth.

Most healthcare professionals rely on criteria in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) developed and published by the American Psychiatric Association (2013) to diagnose patients with substance abuse. In particular, the DSM-5 includes 12 questions that relate to substance use and related behaviors over the past 12 month period. The questions include continuing to use substances when consumption causes employment, interpersonal, and health problems; tolerance;[6] and forgoing important social, employment, or recreational activities in favor of substance use. Individuals who report two or more of these outcomes/behaviors are typically classified as suffering from substance abuse.

Although in many cases substance abuse is a chronic condition and therefore cannot be 'cured', substance abuse can be successfully managed, that is allowing individuals to stop abusing substances and lead productive lives, through suitable treatment (National Institute on Drug Abuse 2012). Depending on the particular substance, treatment may begin with detoxification, a process (often assisted by medications to ease withdrawal symptoms) that allows the body to clear itself of alcohol and/or drugs (National Institute on Drug Abuse 2012).

After detoxification clears the patient's system of substances, there are a wide range of available treatment options. For example, counselling (individual, group, or family); self-help programs (e.g., Alcoholics or Narcotics Anonymous); outpatient care that can include educational classes, receiving treatment in a private doctor's office (e.g., buprenorphine for

[5] The clinical term used by SAMHSA is 'substance use disorder'. However, we use the term 'substance abuse' in our manuscript as this term is commonly used outside clinical settings and may be more appropriate given the large number of criminal justice referrals to specialty substance abuse treatment who do not necessarily meet DSM criteria. For example, 39% of admissions in our sample are referred through the criminal justice system.
[6] Requiring the user to consumer a large quantity of the substance to obtain the same level of intoxication.

opioid addiction), or intensive outpatient treatment that requires the patient to attend classes at a specialized substance abuse treatment facility several hours a day for an extended period; care received in a residential setting for extended periods of time; and inpatient hospital care.

We focus on specialty substance abuse treatment in our study. This treatment modality is defined by SAMHSA as a specialty treatment facility such as a hospital, a residential facility, an outpatient treatment facility, or other facility with a treatment program that offers: (i) outpatient, inpatient, or residential/rehabilitation treatment; (ii) detoxification treatment; (iii) opioid treatment; or (iv) halfway-house services that includes substance abuse treatment (Substance Abuse and Mental Health Services Administration 2014). While specialty care is clearly not the only treatment modality available to patients (National Institute on Drug Abuse 2012), it is a costly modality – both financially and non-financially in terms of the patient's time. Moreover, this modality is heavily financed through government sources (Levit et al. 2013; Substance Abuse and Mental Health Services Administration 2014) and reflects the majority of substance abuse care received (Center for Behavioral Health Statistics and Quality 2016).[7]

2.3 Related literature on the relationship between recessions and substance abuse

Economists have explored how substance use (e.g., any use, binge drinking, heavy drinking, drinking and driving) varies across the business cycle and this literature has produced a wide range of estimates for the direction and magnitude of the relationship; see Pacula (2011) for

[7] The 2015 National Survey of Drug Use and Health asks respondents the location of substance abuse treatment received in the past year (respondents can list multiple responses). The percentages are as follows: hospital 19.5%, rehabilitation facility – inpatient 27.8%, rehabilitation facility – outpatient 48.0%, mental health center – outpatient 29.1%, emergency room 9.4%, private doctor's office 18.3%, self-help group 50.3, and prison 8.4%. The share of treatment received in a specialty treatment facility is 59% when considering hospital, rehabilitation facility – inpatient, rehabilitation facility – outpatient, and mental health center – outpatient as specialty care. Many mental health centers also deliver specialty substance abuse treatment given the high degree of comorbidity across these two conditions. For example in the 2015 National Survey on Substance Abuse Treatment Services, which is administrated by SAMHSA and collects detailed service offering information on the near universe of licensed specialty substance abuse treatment facilities, 34% of facilities list mental health as their primary focus. More details available on request.

an excellent review of this literature. While consensus has not been reached on the relationship between recessions and substance use, a series of economic studies provides convincing evidence that substance abuse, at least for several substances including alcohol and opioids, increases during recessions. Given that we focus on admissions to specialty substance abuse treatment, the linkage of substance abuse and recessions is most important for our purposes.

Davalos, Fang, and French (2012) leverage data from the 2001/02 and 2004/05 National Epidemiological Survey of Alcohol and Related Conditions (NESARC) and show that a one percentage point increase in the state unemployment rate leads to 1.17 greater odds of alcohol abuse and/or dependence. Using internet search data Frijters et al. (2013) document that during recessions searches for alcohol abuse-related terms increase. In particular, the authors show that a 5% increase in unemployment leads to a 15% increase in searches for alcohol abuse-related terms. Carpenter, McClellan, and Rees (2017) draw data from the 2002 to 2013 National Survey of Drug Use and Health (NSDUH) to explore how drug abuse responds to recession. Although Carpenter and colleagues findings were somewhat mixed, they show that the abuse of analgesics and hallucinogens increases during recessions. Hollingsworth, Ruhm, and Simon (2017) find that a 1 percentage point increase in the county unemployment rate leads to a 3.6% increase in the opioid overdose death rate and a 7.0% increase in the opioid-related emergency department (ED) rate, which proxies for non-fatal opioid overdoses. The authors show comparable, although somewhat smaller, increases in overall drug-related overdose deaths and ED visits during recessions, suggesting that the increases in substance-abuse related overdoses and ED visits are not limited to opioids. Overall, the economic evidence suggests that during recessions substance abuse, across a range of substances, increases and thus need for treatment may also increase.

In terms of the impact of recessions on substance abuse treatment, there are two related epidemiological studies. Storti et al. (2011) evaluate how outpatient illicit drug treatment respond to recessions in Europe. The authors find that admissions decline modestly during recessions. Cantor, Stoller, and Saloner (2017) assess the effect of state unemployment rates on treatment settings, accepted payment forms, charity care, offered services, special programs, and use of pharmacotherapies by U.S. specialty substance abuse treatment providers. The authors find that an increase in the unemployment rate leads lower patient volumes (measured by the number of patients treated per day) and an increase in acceptance of private insurance.

We build on the premise established by the extant economic and epidemiological studies by investigating admissions to specialty treatment and heterogeneity across substances of abuse. Of additional importance is that we utilize 24 years of data to explore these relationships. Access to a long time-series is critical from a methodological standpoint as it helps establish the presence of a relationship as described in Ruhm (2015). Indeed, Ruhm cautions that reliance on shorter time-series (less than 15 years) can lead to biased parameter estimates.

3. Data and methods

3.1 Treatment Episode Data Set (TEDS)

We utilize data on admissions to specialty SUD treatment from the TEDS 1992-2015. The TEDS is an administrative database compiled annually by the U.S. government in collaboration with state substance abuse agencies. TEDS includes information on roughly two million admissions to specialty substance treatment each year, and contains nearly the universe of specialty substance abuse treatment facilities that receive financing from the state or federal government, are certified by the state to provide specialty substance treatment, or are tracked for some other reason. Within this dataset we focus on specialty substance abuse treatment.[8] Note that because of this data feature, we do not capture substance abuse treatment received in private doctors' offices or self-help treatment, or providers that accept only cash and/or private health insurance.[9] Moreover there are some differences across states in terms of what admissions are reported to TEDS (Substance Abuse and Mental Health Services Administration 2016).

In our view, even with the above-noted caveats in mind, the TEDS are the best available data to examine how admissions to specialty substance treatment in the U.S. responds to recessions. Indeed, the TEDS are commonly employed within the economics literature to study specialty substance abuse treatment (Anderson 2010; Jena and Goldman 2011; Dave and Mukerjee 2011; Saloner et al. 2017; Powell, Pacula, and Jacobson 2015; Maclean and Saloner 2017; Pacula et al. 2015) and are utilized by the Federal government to estimate the costs of substance abuse treatment to the U.S. economy (Office of National Drug Control Policy 2012). Moreover, Gfroerer et al. (2014) document that the demographics of patients in receiving care in TEDS-tracked facilities are comparable to individuals receiving substance abuse treatment in the nationally representative NSDUH. These findings suggest that the TEDS are generalizable to the specialty substance abuse treatment-seeking population in the U.S., which is precisely our target population. Finally, the TEDS are available over a long time period (1992-2015) and contain consistent measures of substance abuse treatment, these data features are important for studying the health effects of recessions (Hollingsworth, Ruhm, and Simon 2017; Ruhm 2015).

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[8] The specific settings in the TEDS are as follows: detoxification (hospital, ambulatory, or free standing facility); rehabilitation/residential programs in hospitals, short-term ($\leq$30 days), or long-term (>30 days), ambulatory intensive or non-intensive (intensive is treatment 'lasting two or more hours per day for three or more days per week'; non-intensive is 'treatment services including individual, family, and/or group services, and may include pharmacological therapies).
[9] Unless these providers operate in a state that requires reporting to TEDS for some reason.

The 1992 to 2015 TEDS include 42,901,509 specialty substance abuse treatment episodes, the number of episodes per year are reported in Appendix Table 1. An episode can include detoxification services only, outpatient care, or inpatient care received in a hospital or free-standing residential facility. We refer to each specialty substance abuse episode as an 'admission'; although we realize that some episodes may not lead to an actual admission.

We exclude admissions that occur outside the 50 states and D.C., and for which the primary substance is missing or not listed. A non-trivial fraction of the TEDS admissions are referred to treatment from the criminal justice system; roughly 39% during our study period. In our core analyses, we report results based on the full sample of admissions, regardless of referral source. We are concerned that during recessions public financing for policing services may decline which could alter the number or composition of admissions referred from the criminal justice system. Selecting our sample on referral source could lead therefore to conditional-on-positive bias in our regression coefficient estimates. However, admissions referred from the criminal justice system are more likely to be coerced than voluntary and thus are less likely to be determined by factors outlined in traditional economic models of consumer choice (Dave and Mukerjee 2011). To explore this possibility, in robustness checking, we report results generated in the sample of admissions not referred from the criminal justice system and document that our findings are not sensitive to excluding criminal justice system admissions.

We aggregate the TEDS to the state/year level for computational ease. Not all states report information in all years. Appendix Table 1 reports the states not reporting to TEDS by year, this number ranges zero to five. We measure the total number of admissions and total number of admissions by substance of abuse. Specifically, we construct separate admission counts (based on the primary substance listed at admission) for alcohol, cocaine, marijuana, heroin, prescription opioids (e.g., prescription opioid pain relievers such as oxycontin), hallucinogens, stimulants, sedatives, tranquilizers, inhalants, and substances not classified elsewhere (e.g., other-the-counter medications and ketamine). Appendix Table 2 lists substances included in each category. We convert admissions counts to rates per 100,000 residents in the state using population data from the U.S. Census (University of Kentucky Center for Poverty Research Center 2016). We take the logarithm of each outcome variable to address skewness (our outcomes are highly left skewed), thus regression coefficient estimates have the interpretation as an approximation to the percent change.

3.2 Economic conditions data

Our proxy for economic conditions is the annual state unemployment rate from the Bureau of Labor Statistics Local Area Unemployment Rate Database.[10] This variable is a standard measure of economic activity within the literature that explores the effect of recessions on health outcomes, in particular studies examining substance abuse (Ruhm 2000; Hollingsworth, Ruhm, and Simon 2017; Lindo 2015; Carpenter, McClellan, and Rees 2017).

3.3 State-level characteristics

Admissions to specialty substance abuse treatment are determined by myriad factors outside the prevailing economic conditions. We attempt to control for such factors in our regression models. In particular, we seek to include factors that are correlated with both admissions to specialty substance abuse treatment and economic conditions in efforts to mitigate

[10] As noted by Lindo (2015) there are inherent trade-offs in selecting the level of aggregation for analyses of the effect of recessions on health. We choose to use the state over more dis-aggregated measures (e.g., county) for two reasons. (i) We are concerned that, due to limited supply of substance abuse treatment (Buck 2011), many individuals may seek treatment outside of a smaller geographic unit, and our data only allow us to observe where the patient receives treatment, not where the patient resides. Thus, a smaller unit of aggregation may lead to measurement error. (ii) As we note later in the manuscript, the smallest geographic unit available in the public use TEDS is the Core-Based Statistical Area and this measure is not defined for rural areas (<10,000 residents), leading us to omit rural treatment. We return to this issue more formally in robustness checking reported in Section 5.

omitted variable bias in our regression coefficients. We include variables that proxy for state preferences towards substances and addiction treatment: marijuana decriminalization (Pacula, Chriqui, and King 2003),[11] legalization of medical marijuana (Sabia and Nguyen 2016), and a prescription drug monitoring program (Ali et al. 2017). We include two policies that arguably capture social preferences toward providing support for vulnerable populations (the maximum monthly Temporary Aid for Needy Families [TANF] for a family of four and the Earned Income Tax Credit [EITC] state-to-federal ratio) and an indicator for a Democrat governor (University of Kentucky Center for Poverty Research Center 2016). Finally, we control for state demographics from the Current Population Survey (Flood et al. 2017): age, sex, race/ethnicity, and education.

3.4 Methods

To estimate the impact of recessions on admissions to specialty substance abuse treatment the following differences-in-differences we use the following regression model:

(1) $$A_{st} = \alpha_0 + \alpha_1 U_{st-1} + \alpha_2' X_{st} + \theta_s + \tau_t + \Omega_{st} + \varepsilon_{st}$$

This model is comparable to specifications used in other recent analyses of the effects of recessions on substance abuse outcomes (Hollingsworth, Ruhm, and Simon 2017; Carpenter, McClellan, and Rees 2017). The dependent variables is A_{st}, which represents an admission outcome in state *s* in year *t*. In terms of explanatory variables, U_{st-1} is the unemployment rate in state *s* in year *t*, and X_{st} is a vector of time-varying state demographics and policies.[12] Finally, θ_s is a vector of state fixed effects, τ_t is a vector of year fixed effects, Ω_{st} is a state-specific linear time trend,[13] and ε_{st} is the error term. We estimate all regressions with (unweighted) OLS and standard errors are clustered around the state (Bertrand, Duflo, and Mullainathan 2004).

[11] We thank Rosalie Pacula for sharing an updated version of the marijuana decriminalization coding scheme.
[12] Results are not appreciably different if we remove the vector of observable state characteristics.
[13] That is we interact each state fixed effect with a linear time trend that takes on the value of 1 in 1992, 2 in 1993, and so forth.

The appropriate lag structure between admissions to specialty substance abuse treatment and the state unemployment rate in our context is not obvious *ex ante*. Previous literature on recessions and substance abuse shows that changes in the current unemployment rate are linked with changes in substance abuse (Hollingsworth, Ruhm, and Simon 2017; Carpenter, McClellan, and Rees 2017). We hypothesize that changes in the unemployment rate first leads to changes in substance abuse which then, after some period of time, leads to changes in admissions to substance abuse treatment. Hence, in our primary specification, we chose to lag the unemployment rate by one year. However, in robustness checking we also report results using alternative lag structures (no lag, two lags, and three lags).

4. RESULTS

4.1 Summary statistics and trends

Before proceeding to our main analyses, we provide some descriptive evidence on the characteristics of patients receiving specialty substance abuse treatment within TEDS-tracked facilities. Specifically, we examine age, sex, race, ethnicity, education, employment status, living arrangements, prior receipt of substance abuse treatment, and referral source. Results are reported in Table 1. Overall these statistics suggest that patients receiving care in TEDS-tracked facilities are less advantaged than the general U.S. population. For instance, 79% have a high school diploma or less, 69% are unemployed or not in the labor force, and 35% are homeless or reside in a supervised living facility. The sample is relatively young, 96% is less than 55 years of age. The sample is more racially diverse than the U.S. population as whole. Finally, a majority (54%) of the sample has received previous specialty substance abuse treatment and 39% is referred to treatment through the criminal justice system.

Table 2 reports summary statistics for our outcome and control variables. Admissions to specialty substance abuse treatment are 674 per 100,000 over our study period. Alcohol is the most commonly reported substance of abuse at admission (345 per 100,000) followed by marijuana (97 per 100,000), heroin (80 per 100,000), cocaine (68 per 100,000), stimulants (41 per 100,000), prescription opioids (33 per 100,000), sedatives (5 per 100,000), hallucinogens (2 per 100,000), and inhalants (1 per 100,000). There are 3 admissions per 100,000 for other drugs not otherwise classified. The mean lagged state unemployment rate is 5.7%. In terms of policies, 25% of state/year pairs have decriminalized marijuana over this time period, 18% permit medical marijuana, and 49% have implemented prescription drug monitoring programs.

We report trends in the total number of admissions per 100,000 to specialty substance abuse treatment in Figure 1. We observe that admissions are relatively flat 1992 to 2005, ranging between 650 and 700 admissions per 100,000. Over the period 2006 to 2010 admissions surge, peaking at nearly 750 per 100,000 in 2009/2010. This is a period in which prescription opioid drug abuse increased rapidly. Admissions decline monotonically over the period 2011 to 2014 followed by an uptick in 2015.

Figure 2 reports the average lagged state unemployment rate during our study period (1992 to 2015, thus unemployment rates correspond to the period 1991 to 2014). This period encompasses three recessions: the mild recessions of 1991-1992 and 2001-2002, and the severe recession ('Great Recession') of 2008-2010 (National Bureau of Economic Research 2010). In addition, we capture two growth periods: the mid- to late-1990s and the mid-2000s. Our study period also includes the recovery from the 2008-2010 recession. Thus, we are able to leverage a broad range of variation in economic conditions in our study.[14]

[14] Of course, because we rely on differences-in-difference regression models, the variation we use for identification of treatment effects is within-state variation.

Comparing trends in admissions and the lagged state unemployment rate (i.e., Figures 1 and 2) does not reveal an obvious relationship between the two variables. However, we next to turn to our regression analysis to study this question more rigorously and to explore heterogeneity across substances of abuse.

4.2 Admissions regressions

Table 3 reports selected results from our differences-in-differences analyses of admissions to specialty substance abuse treatment. When considering all substances, we find no statistically significant evidence that recessions lead to changes in the number of admissions to specialty substance abuse treatment. Although the coefficient estimate is negative (-0.017) suggesting that total admissions may decline during recessions.

In terms of heterogeneity across substances, for the majority of the substances we consider there is no statistically significant evidence that recessions lead to changes in admissions to specialty substance abuse treatment. In particular, there is no statistically significant effect for alcohol, cocaine, marijuana, prescription opioids, hallucinogens, sedatives, and inhalants. As is the case when we consider all substances, the majority of coefficient estimates are negative which suggests that recessions may lead to declines in admissions.

There are three exceptions to this pattern, however. We find a statistically significant decrease in admissions for heroin (a one percentage point increase in the lagged state unemployment rate leads to an 8.4% decrease in admissions for this substance), a statistically significant increase in admissions for stimulants (a one percentage point increase in the lagged state unemployment rate leads to a 7.0% increase in admissions for this substance), and admissions substances not classified elsewhere (a one percentage point increase in the lagged state unemployment rate leads to a 6.9% decline in admissions for such substances).

While the underlying mechanisms behind this heterogeneity across substances (similar heterogeneity has been identified in other studies such as Carpenter, McClellan, and Rees (2017) and Hollingsworth, Ruhm, and Simon (2017)) is obviously important for both policymakers and providers, the TEDS data will not allow us to fully investigate this important question. However, we can propose hypotheses that may, at least partially, explain the observed heterogeneity.

First, there may be substance substitution effects associated with recessions; that is individuals may abuse different substances at different points of the business cycle due to factors such as income, price, or access. Second, different types of individuals abuse different types of substances; for example those who abuse marijuana may simply differ from those who abuse heroin, stimulants, and other substances. These groups may – for myriad reasons such as employment or insurance coverage – respond differently to recessions in terms of their demand for specialty substance abuse treatment. Third, the decline in heroin admissions may be due to increased mortality among heroin abusers during recessions (Hollingsworth, Ruhm, and Simon 2017). Fourth, there may be differences in risk for treatment across substances. For example, stimulants include methamphetamine, which is linked with violent behavior and paranoia that can plausibly be easily observed by others (National Institute on Drug Abuse 2017), leading to a higher transition rate from abuse into treatment for stimulants than other substances.

5. Robustness checks

We next report results of several robustness checks that probe the sensitivity of our findings to alternative specifications.

5.1 Dynamics

In our core regression models we use the contemporaneous state unemployment rate. However, the specific timing between changes in economic conditions and changes in demand for specialty substance abuse treatment is *ex ante* unknown. To explore the stability of our results to different lag structures, we re-estimate Equation (1) using the contemporaneous unemployment rate, two year lags in this rate, and three year lags in this rate. We report results in Appendix Table 3. Our finding for all substances is largely unchanged across models that employ alternative lag structures: coefficient estimates range from -0.0103 to -0.0282, suggesting that admissions may decline during recessions, but are imprecise in all specifications.

Our finding that heroin (substances not classified elsewhere) admissions decline (increase) during recessions is stable across specifications: coefficients range from -0.0580 to -0.0791 (-0.0547 to -0.0867; although the coefficient is not precise when the contemporaneous unemployment rate is used). The coefficient estimate in the stimulant admission regression is similar when we use the contemporaneous unemployment rate ($\hat{\alpha}_1$= 0.0776) but decreases in magnitude and becomes statistically indistinguishable from zero when we apply more distal lags in the unemployment rate (two and three). Interestingly, when we apply more distal lag structures (two and three lags) we find stronger, and precisely estimated, evidence that admissions for marijuana, prescription opioids, hallucinogens, and inhalants decline when the state unemployment rate increases. As noted earlier, the particular time dynamics between recessions and admissions to specialty substance abuse treatment is unknown *ex ante.*

5.2 Alternative controls for between-state differences

Equation (1) utilizes observable state characteristics (e.g., demographics), state fixed-effects, and state-specific linear time trends to account for between-state heterogeneity. However, the ideal specification is unknown *a-priori*. If there are no omitted variables at the state-level that are correlated with both the state unemployment rate and admissions to specialty substance abuse treatment, then this empirical specification would 'throw away' a substantial degree of variation in state unemployment rates. On the other hand, if our controls do not adequately account for between-state heterogeneity, then our estimates may be biased.

To explore this possibility, we re-estimate Equation (1) using alternative controls for between state differences. First, we control for state-level policies and demographics, year fixed effects, and state fixed effects (Model 1). Second, we control for state-level policies and demographics, year fixed effects, state fixed-effects, and state-specific quadratic time trends (Model 2). Results are reported in Appendix Table 4. Overall, the parameter estimates are in line with our main findings (Table 3). Not surprisingly, the estimated regression coefficients are larger (smaller) in specifications that offer more (less) ability to control for heterogeneity.

5.3 Alternative measures of economic conditions

In our main analyses we use the state unemployment rate to proxy for economic conditions. However, Lindo (2015) shows that analyses of economic conditions can be sensitive to the level at which these conditions are measured. In particular, analyses that rely on state-level measures tend to produce larger coefficient estimates than analyses that rely on lower levels of aggregation. Thus, in addition to the above robustness checks for economic conditions we also re-estimate Equation (1) using the unemployment rate specified at the finest level of aggregation available in the TEDS: the Core-Based Statistical Area (CBSA). Note that this variable is not available for rural areas (<10,000 residents), and thus we lose roughly 25% of our sample. In these models we replace the state fixed effects and the state-specific trends with CBSA equivalents. Given well established shortages of specialty substance abuse treatment (Carr et al. 2008; Buck 2011) and in particular within rural communities (Hyde 2013), relying on smaller areas may not accurately reflect the treatment facilities patients consider when they are determining where to receive substance abuse treatment.

Results from this analysis are reported in Appendix Table 5. Findings are broadly in line with our main findings (see Table 3). However, as documented by Lindo, the estimates are generally smaller when we use finer levels of aggregation and less likely to be statistically different from zero. Interestingly, we find that the estimate for prescription opioid admissions is precisely estimated: a one percentage point increase in the lagged unemployment rate leads to a 1.3% increase in admissions for this substance.

5.4 Non-criminal justice system referrals

Thus far in our analysis we include all admissions, regardless of referral source. However, admissions from the criminal justice system may be less responsive to changes in factors outlined in models of consumer choice (Dave and Mukerjee 2011). We next re-estimate Equation (1) excluding admissions referred through the criminal justice system. We note that, if policing budgets decline during recessions, then the number and composition of individuals referred through criminal justice system sources may be altered, which could lead to conditional-on-positive bias. With this caveat in mind, we report results from this restricted analysis sample in Appendix Table 6. Results are not appreciably different from our main findings (Table 3).

5.5 Population weighting

Our results thus far are unweighted. However, there is some controversy within the economics literature as to whether weights should be applied in analyses seeking to recover causal estimates (Solon, Haider, and Wooldridge 2015; Angrist and Pischke 2009). Thus, we estimate a weighted variant of Equation (1). More specifically, we use the state population to weight this equation. Results are reported in Appendix Table 7 and are not appreciably different from unweighted results; although we note that the estimated coefficients are somewhat smaller.

5.6 Balanced sample

Our results presented thus far are based on the unbalanced sample (Appendix Table 1). However, it is plausible that economic conditions could lead to changes in the propensity for states to report specialty substance abuse treatment admissions data to SAMSHA, leading to year-to-year changes in the composition of states in our sample that is linked to our treatment variable (state unemployment rates). Hence, we re-estimate our regression models on the balanced sample (i.e., the sample of states that appear in TEDS in all years). Results are reported in Appendix Table 8 and are not appreciably different from our main findings. However, we note that the stimulant admissions coefficient is no longer precise.

5.7 Other robustness checks

We focus our analysis on specialty substance abuse treatment, which reflects several modalities of treatment but not a complete enumeration of treatment options available to patients. It is plausible that other modalities (e.g., self-help or office-based care) are more responsive to recessions than specialty care. To explore this possibility we examine two additional data sets: (i) the NESARC 2001/2002 and 2004/2005 to study the effects of economic conditions on non-specialty substance abuse treatment[15] and (ii) the Medicaid State Drug Use Database (SDUD) and examine Food and Drug Administration approved prescription medications used to treat substance abuse within Medicaid (Maclean and Saloner 2017; Mark et al. 2015).[16] Neither of these datasets produce results that recessions lead to changes in these forms of treatment. Results are available on request from the corresponding author.

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[15] Defined as Alcoholics or Narcotics Anonymous; family or social service agency; detoxification ward or clinic; emergency room; halfway house or therapeutic community; crisis center; employee assistance program; religious leader; private physician, psychologist, psychiatrist, social worker, or other professional; and other.

[16] We note that neither of these extensions is optimal. The NESARC is limited to just two time periods covering a relatively strong economic period and the SDUD covers prescription medications purchased through online and retail pharmacies for which Medicaid was a third-party paper; thus these data allow us to study the Medicaid population only. However, examining whether use of these forms of treatment within these time periods and populations can shed light on the extent which our focus on specialty substance abuse treatment limits our analysis.

6. Discussion

Health economists have examined the complex relationship between recessions and health and health behaviors for over two decades (Ruhm 1995, 2015, 2000). However, to the best of our knowledge, only a handful of studies have explored the relationship between economic conditions and measures of substance abuse in the U.S. (Davalos, Fang, and French 2012; Hollingsworth, Ruhm, and Simon 2017; Frijters et al. 2013; Carpenter, McClellan, and Rees 2017), and no studies have investigated the relationship between recessions and admissions to specialty substance abuse treatment. The available literature on substance abuse and recessions suggests that, for a broad set substances, there is evidence that substance abuse worsens during economic downturns. In this study, we evaluate the corresponding impact of recessions on admissions to specialty substance abuse treatment in the U.S. All else equal, we expect an increase in substance abuse to translate into increased admissions. However, due to numerous factors related to the nature of substance abuse, patients receiving substance abuse treatment, and substance abuse treatment delivery system, this relationship is *ex ante* unclear.

When we consider all substances collectively, we find no statistically significant evidence that changes in economic conditions leads to changes in admissions to specialty substance abuse treatment. However, aggregating across substances of abuse masks important and policy relevant heterogeneity. Indeed, we find that admissions for heroin and other drugs not classified elsewhere decline while admissions for simulants increase during recessions.

In interpreting these results a number of limitations should be noted. First, admissions to substance abuse treatment is a function of both supply and demand. Our reduced form methods cannot separate supply from demand side factors. It is plausible that during recessions public financing – the primary source of funding – available for specialty substance abuse treatment may decline which prevents individuals from entering treatment and, based on the economic studies discussed earlier, that substance abuse increases during recessions. Second, the substance abuse treatment providers in the TEDS disproportionally receive public financing. Thus, the extent to which our findings generalize to other settings is unclear. However, given that specialty substance abuse treatment is heavily supported by the public sector we suspect that our findings are potentially generalizable to a large share of the specialty care that is delivered. Indeed, Dave and Mukerjee (2011) state that TEDS captures approximately 67% of such providers. Finally, we do not have objective measures quality of care, expenditures, and length of stay. Thus, we cannot explore how quality or intensity of treatment changes across the business cycle. However, recent epidemiological work by Cantor, Stoller, and Saloner (2017) does not imply that there are large changes in quality of care across the business cycle.[17]

Given these limitations, policymakers and providers may find our results useful. Recessions may lead to increases in untreated substance abuse which can, in turn, lead to increases in mortality and social costs such as crime, healthcare use, and poor employment outcomes. For example, Hollingsworth, Ruhm, and Simon (2017) show that during recessions overdose deaths increase. While we cannot fully test this hypothesis, it is plausible given that there are effective methods available to treat addiction (Volkow et al. 2014; Swensen 2015; Murphy and Polsky 2016), that expanded substance abuse treatment may have prevented some of these deaths. Thus, directing government resources toward substance abuse treatment during recessions may have social benefits.

[17] However, we note that measuring quality of substance abuse treatment in available datasets is challenging.

Table 1. Characteristics of patients receiving specialty substance abuse treatment: TEDS 1992 to 2015

Variable:	Proportion
12-20 years	0.15
21-39 years	0.56
40-54 years	0.25
55+ years	0.04
Male	0.68
Female	0.32
White	0.69
African American	0.19
Other race	0.12
Hispanic	0.10
Non-Hispanic	0.90
Less than high school education	0.37
High school education	0.42
Some college education	0.17
College education	0.05
Employed	0.31
Unemployed	0.35
Not in the labor force	0.34
Homeless	0.12
Supervised living facility	0.23
Independent residence	0.64
No prior treatment	0.46
Prior treatment	0.54
Criminal justice system referral	0.39
Non-criminal justice system referral	0.61
Observations	1187

Notes: Unit of observation is a state/year.

Table 2. Summary statistics: TEDS 1992 to 2015

Variable:	**Mean/proportion**
Admissions per 100,000	
Total	674.0
Alcohol	345.3
Cocaine	67.6
Marijuana	96.9
Heroin	79.8
Prescription opioids	32.5
Hallucinogens	2.44
Stimulants	40.8
Sedatives	4.59
Inhalants	0.77
Substances not classified elsewhere	3.17
State economic conditions	
State unemployment rate, lagged one year	5.71
State-level policies and characteristics	
Marijuana decriminalized	0.25
Medical marijuana permitted	0.18
Prescription drug monitoring program	0.49
EITC state-to-federal ratio	0.051
TANF maximum monthly benefit for a family of4 ($)	624.9
Democrat governor	0.46
Age	0.27
Female	0.51
Male	0.49
White	0.82
African American	0.11
Other non-White race	0.00
Hispanic	0.70
Less than high school education	0.36
High school education	0.25
Some college education	0.21
College graduate	0.18
Observations	1187

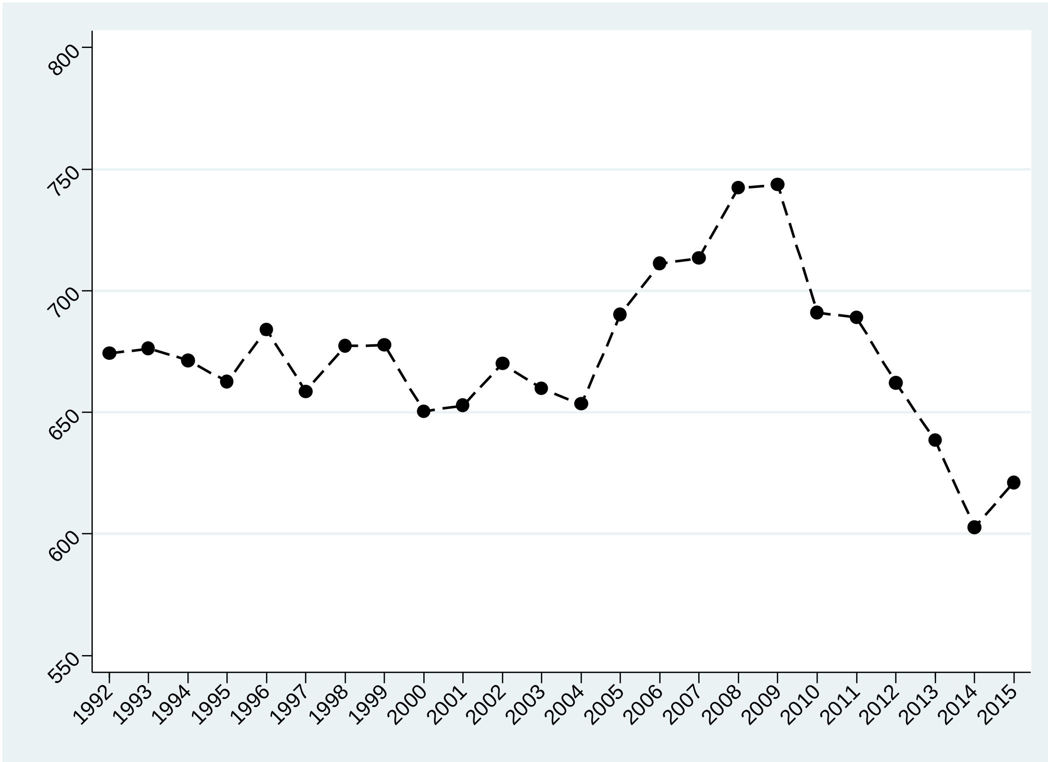
Notes: Unit of observation is a state/year.

Table 3. Effect of the lagged state unemployment rate on admissions per 100,000 to specialty substance abuse treatment: TEDS 1992-2015

Substance:	Estimate (standard error)
Sample mean	674.0
All substances	-0.0173
	(0.0188)
Sample mean	345.3
Alcohol	-0.0174
	(0.0200)
Sample mean	67.6
Cocaine	0.0078
	(0.0199)
Sample mean	96.9
Marijuana	-0.0100
	(0.0186)
Sample mean	79.8
Heroin	-0.0846**
	(0.0336)
Sample mean	32.5
Prescription opioids	-0.0305
	(0.0273)
Sample mean	2.44
Hallucinogens	-0.0283
	(0.0239)
Sample mean	40.8
Stimulants	0.0704***
	(0.0229)
Sample mean	4.59
Sedatives	0.0090
	(0.0223)
Sample mean	0.77
Inhalants	-0.0216
	(0.0130)
Sample mean	3.17
Substances not classified elsewhere	-0.0692*
	(0.0398)
Observations	1187

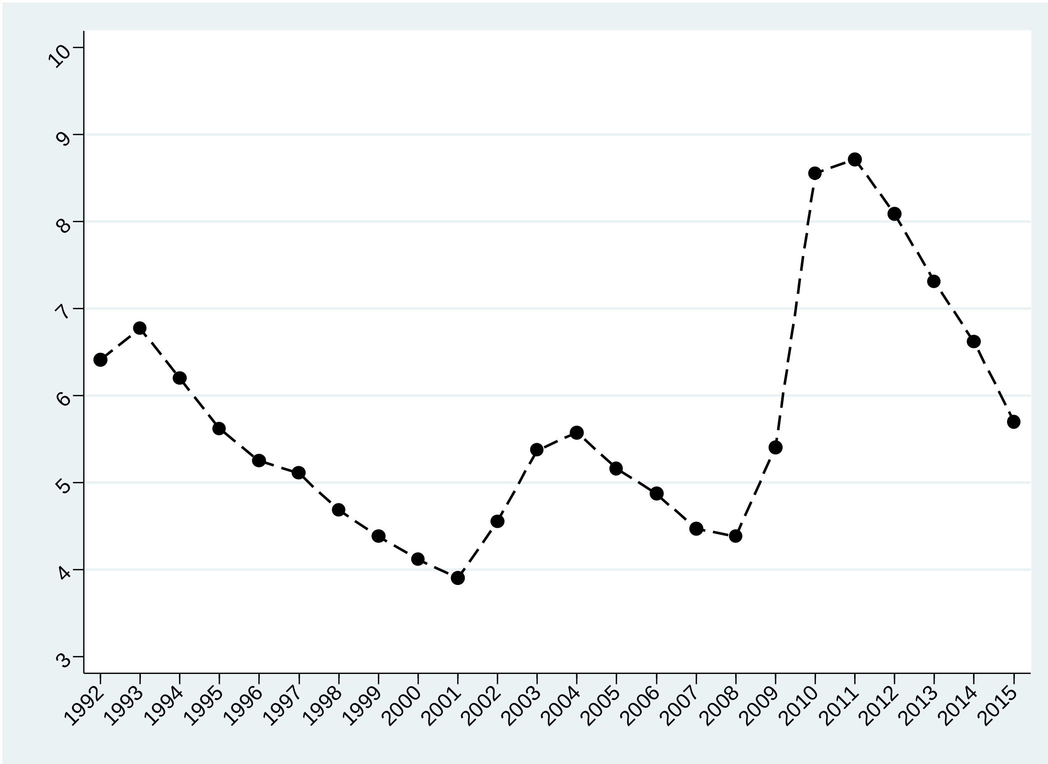
Notes: Unit of observation is a state/year. All models estimated with OLS and control for state policies and demographics, state fixed effects, year fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

Figure 1. Trends in admissions to specialty substance abuse treatment per 100,000: TEDS 1992-2015



Notes: Data are aggregated to the year level. Each data point is the average admissions rate in a given year. Data source is the TEDS.

Figure 2. Trends in the lagged state unemployment rate: BLS 1992-2015



Notes: Data are aggregated to the year level. Each data point is the average lagged (one year) state unemployment rate in a given year. Data source is the Bureau of Labor Statistics Local Area Unemployment Database.

Appendix Table 1. Admissions and states not reporting data by year: TEDS 1992-2015

Year:	Number of admissions	States not reporting
1992	1,560,311	Arizona, Kentucky, Mississippi, District of Columbia
1993	1,618,597	Arizona, Kentucky, Mississippi, District of Columbia
1994	1,671,039	Arizona, Kentucky, Mississippi, Wyoming
1995	1,680,697	Arizona, Kentucky, Wyoming
1996	1,643,731	Arizona, Kentucky, Wyoming
1997	1,607,957	Arizona, Indiana, West Virginia
1998	1,712,268	West Virginia
1999	1,725,885	--
2000	1,747,528	--
2001	1,769,280	--
2002	1,888,786	--
2003	1,864,957	--
2004	1,808,634	Arkansas, District of Columbia
2005	1,896,299	District of Columbia
2006	1,962,666	District of Columbia
2007	1,969,867	Alabama
2008	2,074,988	District of Columbia
2009	2,055,917	Mississippi, District of Columbia
2010	1,932,531	Mississippi
2011	1,936,297	--
2012	1,834,624	--
2013	1,762,106	--
2014	1,639,519	South Carolina
2015	1,537,025	Georgia, Kansas, Oregon, Pennsylvania, South Carolina
Observations	42,901,509	--

Appendix Table 2. Specific drugs in each illicit category: TEDS 1992-2015

Category:	Specific substances:
Alcohol	All forms
Cocaine	Cocaine and crack
Marijuana	Marijuana, hashish, and any other cannabis sativa preparations
Heroin	Heroin
Prescription opioids	Non-prescription methadone, buprenorphine, codeine, Hydrocodone, hydromorphone, meperidine, morphine, opium, oxycodone, pentazocine, propoxyphene, tramadol, and any other drug with morphine-like effects.
Hallucinogens	Phencyclidine, LSD, DMT, STP, hallucinogens, mescaline, peyote, psilocybin, etc.
Stimulants	Methamphetamine, amphetamines, MDMA, phenmetrazine, and other unspecified amines and related drugs, and methylphenidate and any other stimulants
Sedatives	Benzodiazepines: alprazolam, chlordiazepoxide, clonazepam, clorazepate, diazepam, flunitrazepam, flurazepam, halazepam, lorazepam, oxazepam, prazepam, temazepam, triazolam, and other unspecified benzodiazepines. Non- Benzodiazepines tranquilizers: meprobamate, tranquilizers, etc. Barbiturates: amobarbital, pentobarbital, phenobarbital, secobarbital, etc. Hypnotics: chloral hydrate, ethchlorvynol, glutethimide, methaqualone, sedatives/hypnotics
Inhalants	Chloroform, ether, gasoline, glue, nitrous oxide, paint thinner, etc.
Substances not classified elsewhere	Over-the-counter medications: aspirin, cough syrup, diphenhydramine and other anti-histamines, sleep aids, and any other legally obtained non-prescription medication Other: diphenylhydantoin/phenytoin, GHB/GBL, ketamine, etc.

Appendix Table 3. Effect of the state unemployment rate on admissions per 100,000 to specialty substance abuse treatment allowing for alternative dynamics: TEDS 1992-2015

Substance:	No lag	Two lags	Three lags
Sample mean	674.0	674.0	674.0
All substances	-0.0103	-0.0231	-0.0282
	(0.0186)	(0.0223)	(0.0203)
Sample mean	345.3	345.3	345.3
Alcohol	-0.0085	-0.0232	-0.0233
	(0.0193)	(0.0225)	(0.0191)
Sample mean	67.6	67.6	67.6
Cocaine	0.0178	-0.0099	-0.0305
	(0.0206)	(0.0230)	(0.0225)
Sample mean	96.9	96.9	96.9
Marijuana	0.0031	-0.0301	-0.0546**
	(0.0185)	(0.0230)	(0.0230)
Sample mean	79.8	79.8	79.8
Heroin	-0.0770**	-0.0791**	-0.0580**
	(0.0329)	(0.0335)	(0.0285)
Sample mean	32.5	32.5	32.5
Prescription opioids	-0.0142	-0.0409	-0.0444*
	(0.0247)	(0.0289)	(0.0252)
Sample mean	2.44	2.44	2.44
Hallucinogens	-0.0113	-0.0442**	-0.0521***
	(0.0258)	(0.0196)	(0.0192)
Sample mean	40.8	40.8	40.8
Stimulants	0.0776***	0.0272	-0.0346
	(0.0248)	(0.0262)	(0.0290)
Sample mean	4.59	4.59	4.59
Sedatives	0.0034	0.0010	-0.0085
	(0.0210)	(0.0241)	(0.0232)
Sample mean	0.77	0.77	0.77
Inhalants	-0.0178	-0.0251**	-0.0208**
	(0.0136)	(0.0106)	(0.0089)
Sample mean	3.17	3.17	3.17
Substances not classified	-0.0547	-0.0801**	-0.0867**
elsewhere	(0.0384)	(0.0382)	(0.0352)
Observations	1187	1187	1187

Notes: Unit of observation is a state/year. All models estimated with OLS and control for state policies and demographics, state fixed effects, year fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

Appendix Table 4. Effect of the lagged state unemployment rate on admissions per 100,000 to specialty substance abuse treatment allowing for alternative controls for between state differences: TEDS 1992-2014

Substance:	**Model (1)**	**Model (2)**
Sample mean	674.0	674.0
All substances	-0.0215	-0.0130
	(0.0147)	(0.0226)
Sample mean	345.3	345.3
Alcohol	-0.0211	-0.0184
	(0.0162)	(0.0220)
Sample mean	67.6	67.6
Cocaine	-0.0031	-0.0001
	(0.0241)	(0.0243)
Sample mean	96.9	96.9
Marijuana	0.0150	0.0022
	(0.0167)	(0.0201)
Sample mean	79.8	79.8
Heroin	-0.0876**	-0.0282
	(0.0401)	(0.0254)
Sample mean	32.5	32.5
Prescription opioids	-0.0462	0.0109
	(0.0279)	(0.0248)
Sample mean	2.44	2.44
Hallucinogens	-0.0220	-0.0244
	(0.0210)	(0.0171)
Sample mean	40.8	40.8
Stimulants	0.0791***	0.0181
	(0.0260)	(0.0233)
Sample mean	4.59	4.59
Sedatives	0.0299	0.0150
	(0.0196)	(0.0183)
Sample mean	0.77	0.77
Inhalants	-0.0108	-0.0138
	(0.0168)	(0.0119)
Sample mean	3.17	3.17
Substances not classified	-0.0755*	-0.0359
elsewhere	(0.0418)	(0.0330)
Observations	1187	1187

Notes: Unit of observation is a state/year. Standard errors are clustered around the state and reported in parentheses.
Model (1) controls for state policies and demographics, state fixed effects, and year fixed effects.
Model (2) controls for state policies and demographics, state fixed effects, year fixed effects, and state-specific quadratic time trends.
***;**;*=statistically significant at the 1%; 5%; 10%.

Appendix Table 5. Effect of lagged CBSA unemployment rate on admissions per 100,000 to specialty substance abuse treatment: TEDS 1992-2015

Substance:	**Estimate (standard error)**
Sample mean	85.2
All substances	0.0045 (0.0074)
Sample mean	40.8
Alcohol	0.0059 (0.0065)
Sample mean	10.7
Cocaine	0.0016 (0.0050)
Sample mean	11.6
Marijuana	-0.0033 (0.0059)
Sample mean	12.8
Heroin	-0.0041 (0.0050)
Sample mean	3.922
Prescription opioids	0.0125** (0.0049)
Sample mean	0.49
Hallucinogens	-0.0013 (0.0018)
Sample mean	3.86
Stimulants	0.0050 (0.0044)
Sample mean	0.57
Sedatives	0.0026 (0.0024)
Sample mean	0.07
Inhalants	0.0006 (0.0014)
Sample mean	0.34
Substances not classified elsewhere	-0.0092** (0.0044)
Observations	6960

Notes: Unit of observation is a state/year. All models estimated with OLS and control for state policies and demographics, CBSA fixed effects, year fixed effects, and CBSA-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

Appendix Table 6. Effect of the lagged state unemployment rate on admissions per 100,000 to specialty substance abuse treatment excluding admissions referred through the criminal justice system: TEDS 1992-2015

Substance:	Estimate (standard error)
Sample mean	424.2
All substances	-0.0272
	(0.0194)
Sample mean	202.1
Alcohol	-0.0313
	(0.0208)
Sample mean	49.8
Cocaine	0.0045
	(0.0193)
Sample mean	46.1
Marijuana	-0.0115
	(0.0185)
Sample mean	69.4
Heroin	-0.0874**
	(0.0329)
Sample mean	26.5
Prescription opioids	-0.0359
	(0.0275)
Sample mean	1.49
Hallucinogens	-0.0249
	(0.0207)
Sample mean	22.3
Stimulants	0.0607***
	(0.0226)
Sample mean	3.62
Sedatives	0.0089
	(0.0205)
Sample mean	0.53
Inhalants	-0.0144
	(0.0108)
Sample mean	2.32
Substances not classified elsewhere	-0.0619
	(0.0380)
Observations	1187

Notes: Unit of observation is a state/year. All models estimated with OLS and control for state policies and demographics, state fixed effects, year fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

Appendix Table 7. Effect of the lagged state unemployment rate on admissions per 100,000 to specialty substance abuse treatment using population weights: TEDS 1992-2015

Substance:	**Estimate (standard error)**
Sample mean	613.7
All substances	0.0020
	(0.0251)
Sample mean	275.8
Alcohol	0.0050
	(0.0267)
Sample mean	77.4
Cocaine	-0.0005
	(0.0241)
Sample mean	90.6
Marijuana	0.0017
	(0.0228)
Sample mean	94.7
Heroin	-0.0494**
	(0.0229)
Sample mean	27.5
Prescription opioids	0.0358
	(0.0380)
Sample mean	2.12
Hallucinogens	-0.0273*
	(0.0160)
Sample mean	37.1
Stimulants	0.0447*
	(0.0227)
Sample mean	4.82
Sedatives	0.0358*
	(0.0191)
Sample mean	0.54
Inhalants	-0.0242*
	(0.0129)
Sample mean	3.08
Substances not classified elsewhere	-0.0433
	(0.0308)
Observations	1187

Notes: Unit of observation is a state/year. All models estimated with weighted OLS, state population serves as the eights, and control for state policies and demographics, state fixed effects, year fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

Appendix Table 8. Effect of the lagged state unemployment rate on admissions per 100,000 to specialty substance abuse treatment using the balanced sample of states: TEDS 1992-2015

Substance:	**Estimate (standard error)**
Sample mean	717.2
All substances	-0.0150
	(0.0202)
Sample mean	370.7
Alcohol	-0.0181
	(0.0214)
Sample mean	68.6
Cocaine	0.0125
	(0.0214)
Sample mean	99.1
Marijuana	-0.0109
	(0.0193)
Sample mean	94.5
Heroin	-0.0821**
	(0.0391)
Sample mean	34.7
Prescription opioids	-0.0182
	(0.0296)
Sample mean	23
Hallucinogens	-0.0329
	(0.0260)
Sample mean	39.2
Stimulants	0.0801***
	(0.0247)
Sample mean	4.5
Sedatives	0.0290
	(0.0182)
Sample mean	0.8
Inhalants	-0.0199
	(0.0142)
Sample mean	2.9
Substances not classified elsewhere	-0.0506
	(0.0395)
Observations	888

Notes: States that do not appear in all years of the TEDS are excluded: AL, AR, AZ, DC, GA, IN, KS, KY, MS, OR, PA, SC, WV, and WY. Unit of observation is a state/year. All models estimated with OLS and control for state policies and demographics, state fixed effects, year fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses.
***;**;*=statistically significant at the 1%; 5%; 10%.

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