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THE EFFECT OF PUBLIC INSURANCE EXPANSIONS ON SUBSTANCE USE DISORDER TREATMENT: EVIDENCE FROM THE AFFORDABLE CARE ACT

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ABSTRACT

We examine the early effects of U.S. state Medicaid expansions under the Affordable Care Act (ACA) on substance use disorder (SUD) treatment utilization. We couple administrative data on admissions to specialty SUD treatment and prescriptions for medications used to treat SUDs in outpatient settings with a differences-in-differences design. We find no evidence that admissions to specialty treatment changed in expanding states relative to non-expending states. However, post expansion, Medicaid-reimbursed prescriptions for medications used to treat SUDs in outpatient settings increased by 33% in expanding states relative to non-expanding states. Among patients admitted to specialty SUD treatment, we find that in expanding states Medicaid insurance and use of Medicaid to pay for treatment increased by 58% and 57% following the expansion. In an extension to the main analyses we find no evidence that the expansions affected fatal alcohol poisonings or drug-related overdoses. Overall, our findings provide evidence on the early effects of the ACA on SUD treatment utilization with the newly-eligible Medicaid population.

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1. Introduction

This study explores the effect of state Medicaid expansions under the Affordable Care Act (ACA) on substance use disorder (SUD) treatment utilization among low-income adults. This population has historically had little access to insurance but has elevated prevalence of SUDs (Busch et al., 2013). Medicaid is a publicly-funded health insurance program for low-income individuals in the United States, but prior to the ACA most low-income adults were not eligible for the program. The ACA allocated funds for states to expand Medicaid to adults below 138% of the federal poverty level, but the decision to expand Medicaid was left optional for states. We leverage variation in public insurance eligibility generated by U.S. states' decisions to expand Medicaid to these adults between 2010 and 2015.

Problems related to substance use are a major public health concern in the U.S. and other developed countries (World Health Organization, 2017). In 2015, over 20 million individuals in the U.S. met diagnostic criteria for an SUD (Center for Behavioral Health Statistics and Quality, 2015). Studying factors related to SUD treatment is of critical policy importance as the U.S. is the midst of an alarming and unprecedented rise in opioid use disorders, which both the Centers for Disease Control and Prevention and Department of Health and Human Services have classified as an epidemic. Indeed, each day 91 U.S. residents die from an opioid overdose, a quadrupling of the death rate since 1999 (Centers for Disease Control and Prevention, 2016).

SUDs are characterized by clinically significant impairment related to use of alcohol or psychoactive drugs. Symptoms of impairment can include engaging in unintended risky behaviors, experiencing trouble in work or family settings due to substance use, and experiencing physical and psychological symptoms of withdrawal during periods of nonuse (Hasin et al., 2013). Furthermore, millions of Americans who do not meet diagnostic criteria for

SUDs engage in high-risk behaviors such as binge and/or heavy drinking, or nonmedical use of prescription drugs (Center for Behavioral Health Statistics and Quality, 2016).[1] The harms related to substance use are believed to be a leading contributor to declining life expectancy among middle aged white Americans (Case and Deaton, 2015) and to the poor health of Americans relative to citizens of other high income countries (Degenhardt et al., 2013).

In addition to personal costs borne by the affected individual, substance use also contributes to a wide range of costly social problems including elevated healthcare utilization (French et al., 2011, Balsa et al., 2009, Mark et al., 2016), crime and violence (Carpenter, 2005, Markowitz and Grossman, 2000), increased use of social services (Jayakody et al., 2000), traffic accidents (Anderson et al., 2013), and reduced productivity in the labor market (Terza, 2002). Indeed, the social costs of alcohol and drug use on the U.S. economy are estimated to be as high as $519B per year (Caulkins et al., 2014).[2]

While the effectiveness and cost-effectiveness of SUD treatment is well-established (National Institute on Drug Abuse, 2012, Lu and McGuire, 2002, Swensen, 2015, Popovici and French, 2013, Rajkumar and French, 1997), only one-tenth of individuals who meet the diagnostic criteria for SUDs receive treatment in any year (Center for Behavioral Health Statistics and Quality, 2016). Although there are myriad reasons for failure to receive treatment, key barriers to receiving treatment include individuals simply not wishing to stop using

[1] Binge drinking is defined by the U.S. Centers for Disease Control and Prevention as five (four) or more drinks in one drinking sessions for men (women). This organization defines heavy drinking as two (one) or more drinks per day among men (women): https://www.cdc.gov/alcohol/ (accessed February 22nd, 2017). Non-medical use of prescription drugs is defined as defined as the use of these medications without a prescription from a healthcare provider, use in a manner other than as directed (e.g., taking a higher dosage than prescribed), or use only for the medication's psychotropic experience (e.g., euphoria, sedation) (United Nations Office on Drugs and Crime, 2011).

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

substances, lack of insurance coverage, and inability to pay (Center for Behavioral Health Statistics and Quality, 2016).

The ACA provides an opportunity to increase treatment utilization among individuals with SUD and to alter the financing of such treatment. Medicaid expansion provides millions of previously uninsured adults with coverage, and SUD treatment is a required benefit in expansion plans (Beronio et al., 2014). Due in large part to the substantial increases in the number of covered individuals and services, some healthcare scholars argue that 'no illness will be more affected than substance use disorders' by the ACA (McLellan and Woodworth, 2014).

We study the effects of Medicaid expansion under the ACA on treatment utilization and use of Medicaid as source of payment for such treatment. We leverage administrative data drawn from the Treatment Episodes Data Set (TEDS) between 2010 and 2014, and the Medicaid State Drug Utilization Data (SDUD) between 2011 and 2015.[3] TEDS includes nearly nine million admissions to specialty SUD treatment facilities while SDUD captures all prescriptions for medications purchased at retail and online pharmacies used to treat SUDs in outpatient settings financed, at least partially, by Medicaid. We couple these administrative data sets with differences-in-differences regression models.

Our findings suggest that states expanding Medicaid experienced no change in admissions to specialty SUD treatment post-expansion relative to non-expending states. Post-expansion, prescriptions for medications used to treat SUDs financed by Medicaid increased by 33% in expanding states relative to non-expanding states. Among patients receiving specialty treatment, Medicaid insurance coverage increased 58% and use of Medicaid as a form of payment increased by 57% in expanding states relative to non-expanding states, post expansion.

[3] The 2015 TEDS are not available at the time of writing.

In a supplementary analysis, we examine changes in fatal alcohol poisonings and drug-related overdoses from 2010 to 2015. We do not find any evidence of changes in such deaths within expansion states relative to non-expansion states.

This paper is organized as follows: Section 2 outlines our conceptual framework and the related literature. Data, variables, and methods are outlined in Section 3. Results for specialty SUD treatment are reported in Section 4 and results for prescription medications are reported in Section 5. Extensions to the main analysis and robustness checks are listed in Section 6. Finally, Section 7 provides a discussion of the findings and potential policy implications.

2. The Medicaid program, a conceptual framework, and prior research

We next discuss the Medicaid program within the context of the ACA, review a conceptual framework that motivates an economic study of public insurance expansions on demand for SUD treatment, and briefly review the literature on recent Medicaid expansions.

2.1 A brief overview of the Medicaid program and ACA-related program changes

Medicaid was introduced in 1965 as a means-tested insurance program that financed healthcare for low-income individuals. The program, which is currently the largest health insurance program in the U.S. in terms of covered lives,[4] was primarily designed to offer public insurance to vulnerable populations that previously had incomplete access to insurance: poor and disabled individuals. In particular, the initial focus of Medicaid was children and their mothers who qualified for welfare, poor seniors, and the disabled.

The Medicaid program is jointly funded by federal and state governments. While the federal government has established laws and regulations that set minimum standards for the Medicaid program in terms of covered populations and services, states have substantial

[4] http://kff.org/medicaid/fact-sheet/medicaid-pocket-primer/ (accessed March 9th, 2017).

flexibility along several eligibility and coverage dimensions. In 2009, prior to the earliest ACA-related expansions (outlined in a later section), Medicaid insured over 50 million individuals, the majority being children (U. S. Department of Health and Human Services, 2009).

Prior to the ACA, Medicaid was only available to specific categories of low-income individuals and state income eligibility criteria varied widely. As a result, many low-income individuals with substantial health needs were not eligible for their states' Medicaid program (Decker et al., 2013). Pre-ACA simulations indicated that the prevalence of SUDs was substantially higher in the population targeted by Medicaid expansions and that unmet need was higher within this group than populations previously eligible (Busch et al., 2013).

The Medicaid expansion was designed as a national program that would provide enhanced federal funding for all states to cover the newly eligible populations (French et al., 2016). However, the 2012 Supreme Court decision on the ACA left Medicaid expansions optional to the state.[5] Just half the states and DC initially participated in the Medicaid expansion in 2014, although by 2017, 32 states had expanded their program.

2.2 Conceptual framework

The Grossman (1972) model of the demand for health and healthcare services motivates our study. This model is a standard starting point for economic analyses of substance use and demand for healthcare services (Cawley and Ruhm, 2012). We focus on utilization of a particular healthcare service: SUD treatment. Within this framework, consumers do not demand healthcare services *per se*, but instead they demand the health improvements attributable to use of such services. Health is produced by consumers combining market and non-market goods.

[5] *National Federation of Independent Business v. Sebelius*, 567 U.S. ___ (2012), 183 L. Ed. 2d 450, 132 S.Ct. 2566.

Rational consumers maximize a utility function given the price of healthcare services and other goods, preferences, a health endowment, a health production function, additional factors affecting health (e.g., education), and a budget constraint. The quantity of healthcare that consumers demand depends on the utility they obtain from health improvements associated with healthcare use relative to other goods and the associated prices. As with other goods, when its price decreases, consumers are expected to increase the quantity of healthcare demanded.

Health insurance, by lowering the out-of-pocket price faced by consumers, is predicted to increase the quantity of healthcare services demanded. Thus, the Medicaid expansions we study should, all else equal, increase the quantity of SUD treatment demanded. However, there are several factors that are unique to the patients potentially seeking SUD treatment and the providers delivering such care that may mute the predicted increases in quantity demanded.

On the demand side, individuals may delay seeking, or choose not to seek, SUD treatment for reasons other than insurance coverage and ability to pay for treatment. First, in surveys of individuals with SUDs, insurance and financial barriers are less commonly reported as reasons for not seeking care than are factors related to a lack of awareness of own need or an unwillingness to stop using substances (Substance Abuse and Mental Health Services Administration, 2014). Second, stigma could also reduce treatment-seeking among newly insured individuals (Substance Abuse and Mental Health Services Administration, 2014). Third, unlike most healthcare services, a large amount of SUD treatment is received under legal coercion, for example, treatment ordered by a judge as an alternative to jail time (Substance Abuse and Mental Health Services Administration, 2016). Legally coerced treatment is less likely to be driven by insurance coverage than non-economic factors such as the criminal justice system. Fourth, SUD treatment has historically been heavily supported by state and local government funding grants, allowing patients with limited financial resources to receive care for free or at a heavy discount. For example, in 2014 48% of U.S. specialty SUD treatment facilities reported offering free treatment to patients who could not pay and 61% offered sliding scale discounts (Substance Abuse and Mental Health Services Administration, 2015).[6] This form of charity care can act as substitute for paid care (Lo Sasso and Meyer, 2006) and may mute the effect of the Medicaid expansions we study.

While not unique to SUD treatment, having insurance could increase an individual's propensity to engage in risky behaviors such as substance use. One hypothesis is that insurance insulates people from the full healthcare costs of substance use, thereby encouraging such behavior (*ex ante* moral hazard). Gaining insurance could also increase substance use due to the income effect of subsidized health insurance (i.e., lower out-of-pocket spending on healthcare increases disposable income available to purchase alcohol and drugs). Health insurance itself can also be used to gain access to lower-cost addictive medications like opioids, stimulants, and benzodiazepines, which could increase substance use. Barbaresco et al. (2015) show that the dependent coverage mandate, an early ACA provision implemented in 2010 that required many private insurers to cover children of beneficiaries through age 26, increased binge drinking, and Klick and Stratmann (2006) document that state private insurance mandates for SUD treatment may lead to increases in alcohol use disorder. However, to the best of our knowledge, there is no evidence of *ex ante* moral hazard following the ACA-related Medicaid expansions (Courtemanche et al., 2017, Simon et al., 2017).

On the supply side, capacity and financial constraints within the SUD treatment delivery system (Andrews et al., 2015) may limit the ability of providers to meet the increases in the

[6] Authors' calculations based on the 2014 National Survey of Substance Abuse Treatment Services (N-SSATS) data.

quantity of care demanded, at least in the short run. Many SUD treatment facilities may not have any open slots (or financing available to expand treatment slots) to which they can admit patients (McLellan and Meyers, 2004, Jones et al., 2015, Carr et al., 2008). Gaining access to SUD treatment in a private doctor's office may also be challenging. Even though the supply of primary care physicians willing to see Medicaid patients has grown under the ACA, Medicaid acceptance still lags behind private insurance (Polsky et al., 2017). Additionally, physicians waivered to prescribe buprenorphine (a drug used to treat opioid use disorder) are not available in many communities or do not see the authorized number of patients (Stein et al., 2016).

Historically within the U.S. both private and public insurance have offered less generous coverage for SUD treatment relative to general healthcare treatment and many providers simply did not accept insurance of any type (Starr, 2002). Providers operating outside of the insurance system have accepted cash payment and/or relied heavily on grants from states and localities to support free treatment. Such providers may simply lack the administrative capacity required to bill Medicaid. Thus, examining whether newly acquired insurance can be used to pay for treatment by patients is important to understanding whether or not expansions reduce the costs of treatment for patients (Saloner et al., 2017a), and motivates the importance of looking at source of payment for treatment separate from the insurance status of individuals in treatment.

Based on the preceding considerations, we test the following three hypotheses in our analysis. Following Medicaid expansion:

H1: More individuals will receive treatment (both specialty treatment and prescriptions used in outpatient settings) in expanding states relative to non-expanding states.

H2: More patients in specialty SUD treatment will have Medicaid as their insurance coverage in expanding states relative to non-expanding states.

H3: More patients in specialty treatment will use Medicaid to pay for treatment in expanding states relative to non-expanding states.

While we expect these changes to occur in response to Medicaid expansion, it is an open question as to the magnitude of these effects, particularly in the short-run as we examine here.

2.3. Prior literature

A growing literature examines the effects of the ACA-related Medicaid expansions on health insurance coverage, general healthcare use, and health outcomes (Antonisse et al., 2016, French et al., 2016). Wherry and Miller (2016) show that, post-expansion, Medicaid coverage increased by 10.5 percentage points (34%) among U.S. citizens 19-64 years of age with family incomes below 138% of the federal poverty level while uninsurance declined 7.4 percentage points (22%). Moreover, a recent study estimates that the Medicaid expansions we investigate accounted for 60% of the overall ACA coverage increase (Frean et al., 2016).

Several studies document that the ACA-related Medicaid expansion is associated with greater improvements in access to general healthcare services such as primary care visits and reduced unmet need among low-income adults in expanding states versus non-expanding states (Wherry and Miller, 2016, Simon et al., 2017, Sommers et al., 2016b, Mulcahy et al., 2016, Kirby and Vistnes, 2016, Miller and Wherry, 2017). There is less decisive evidence as to whether the ACA-related Medicaid expansion has improved health status. Two studies suggest improvements in some measures of health (Simon et al., 2017, Sommers et al., 2016a) while a third suggests that these expansions had no substantial effect (Courtemanche et al., 2017).

The literature on the ACA-related Medicaid expansions and receipt of SUD treatment is small. To our knowledge, only two prior clinical studies have examined changes in SUD treatment following the ACA Medicaid expansion. Saloner et al. (2017b), using the National

Survey on Drug Use and Health, find not change in SUD treatment between 2010-2013 (pre-expansion) and 2014 (post-expansion), but do find that Medicaid paid for a larger share of treatment in 2014. The authors rely on a pre-post design, and therefore are not able to isolate changes due to Medicaid expansion. Wen et al. (2017) use the Medicaid State Drug Utilization Data (SDUD) – the same dataset we examine in our prescription drug analysis – to test changes in use of buprenorphine between expansion and non-expansion states through 2014. The authors find a 70% increase in the volume of buprenorphine prescriptions reimbursed by Medicaid in expansion states compared to non-expansion states.

The potential impact of the ACA Medicaid expansions may also be gleaned from prior state-level expansions of Medicaid eligibility. In the decade prior to the ACA, several states sought federal waivers to provide Medicaid to otherwise ineligible low-income adults (Rudowitz et al., 2014). These expansions generally restricted eligibility to very low-income individuals and some expansions covered only a limited set of benefits (Bouchery et al., 2012). Overall, these expansions did not result in widespread reductions in the uninsured rate. In two studies Wen and colleagues (Wen et al., 2015, Wen et al., 2014) examine the impact of pre-ACA Medicaid eligibility under these waiver-based expansions. The authors find that expansions decreased unmet need for SUD treatment and increased specialty SUD treatment admissions.

Medicaid expansion under the 2006 Massachusetts health reform law provides another experience analogous to the ACA from which we can potentially learn about the effect of public insurance expansions on SUD treatment utilization. The Massachusetts reform, which expanded both public and private insurance and is viewed by many as a blueprint for the ACA (Gruber, 2008), included a Medicaid expansion with a benefit package that covered a generous set of SUD services. Maclean and Saloner (2017) find that specialty SUD treatment admissions increased in

MA following the reform relative to comparison states, although the estimate is not precisely estimated across all specifications.

In summary, the literature suggests that Medicaid expansions can increase use of SUD treatment and shift financial responsibility of such treatment towards Medicaid, and away from patients and the safety net healthcare system.

3. Data, variables, and methods

3.1. Data on specialty SUD treatment: Treatment Episode Data Set (TEDS)

We use the Treatment Episode Data Set (TEDS) to study specialty SUD treatment. TEDS is an administrative database compiled annually by the U.S. Substance Abuse and Mental Health Services Administration (SAMHSA) in collaboration with state substance abuse agencies. SAMHSA defines a specialty SUD treatment facility as a hospital, a residential SUD facility, an outpatient SUD treatment facility, or other facility with an SUD treatment program that offers: (i) outpatient, inpatient, or residential/rehabilitation SUD treatment; (ii) detoxification treatment; (iii) opioid treatment; or (iv) halfway-house services that include SUD treatment.[7]

TEDS is one component of a broader data inventory maintained by SAMHSA to track the quantity and quality of specialty SUD treatment within the U.S. The TEDS includes information on approximately two million admissions to specialty SUD treatment each year, and contains nearly the universe of specialty SUD treatment facilities that receive financing from the state or federal government, are certified by the state to provide specialty SUD treatment, or are tracked

[7] A common referral source to SUD treatment is the criminal justice system. Indeed, over one third of the admissions in our TEDS analysis data set are referred through this system. As noted earlier in the manuscript, legally coerced admissions may be less responsive to changes in price attributable to a public insurance expansion than other admissions. In unreported analyses, we excluded all admissions referred through the criminal justice system and re-estimated our empirical models (outlined later in the manuscript). Results, available on request, are not appreciably different from results reported in the manuscript.

for some other reason.[8] Thus, TEDS reflect admissions financed by multiple payers (e.g., self-payment, private insurance, Medicaid, Medicare). TEDS is commonly employed within the economics literature to study SUD treatment (Anderson, 2010, Dave and Mukerjee, 2011, Jena and Goldman, 2011, Powell et al., 2015, Pacula et al., 2015, Maclean et al., 2013, Saloner et al., 2016) and is utilized by the Federal government to estimate the costs of SUD treatment to the U.S. economy (Office of National Drug Control Policy, 2012).

While TEDS is not a national probability sample, patients receiving treatment in TEDS-tracked facilities are representative of the broader specialty SUD treatment-receiving population. For example, demographics of patients in TEDS-tracked facilities are comparable to samples of individuals who report past year SUD treatment in the NSDUH (Gfroerer et al., 2014).

We exclude admissions for which the patient is less than 18 years of age as such admissions are not directly affected by the Medicaid expansions we study here, which target adults. A limitation of the TEDS is that not all states report data in each year. Appendix Table 1 reports the states not providing data to TEDS in each year 2010-2014. This number ranges from one to three states, thus the TEDS captures the vast majority of states in all years of our study.[9]

3.2 Data on prescriptions: Medicaid State Drug Utilization Data (SDUD)

An objective of the ACA is to facilitate integration of SUD into general healthcare, for example, providing outpatient treatment in physicians' offices (McLellan and Woodworth, 2014). Such care is not captured in the TEDS which includes specialty care only. To provide broader insight into the effect of the Medicaid expansions on SUD treatment utilization that may occur in office-based settings, we turn to the SDUD. Studying medication treatment prescribed

[8] TEDS does not include treatment received in private physician's offices, facilities that do not receive any public funding, emergency departments, and self-help groups.

[9] In unreported analyses, we re-estimated our regression models on the unbalanced sample of states. Results, available on request, are not appreciably different from those reported here.

by outpatient physicians may also allow us to measure the extent to which newly insured individuals who have SUDs are forming relationships with healthcare providers and becoming integrated with the healthcare delivery system. Given the historical segregation of SUD treatment from the general healthcare delivery system (Buck, 2011), such integration is important for treating overall health and, in turn, patient wellbeing.

The SDUD includes all states' data for outpatient prescription medications covered under the Medicaid Drug Rebate Program (U.S. Department of Health and Human Services, 2012). Since 1992, state Medicaid programs have been compelled to submit data on the number and type of prescriptions filled each quarter to the Centers for Medicare & Medicaid Services (CMS) in exchange for federal matching funds. We use data from 2011 to 2015 in our study and aggregate the SDUD to the state-year level.[10,11]

We focus on medications approved by the Food and Drug Administration (FDA) for the treatment of SUDs: buprenorphine, naltrexone, acamprosate, disulfiram, and topiramate.[12] We do not include methadone, which is a standard treatment for opioid use disorder, as methadone purchased through a pharmacy is typically utilized to treat chronic pain (Office of the Inspector General Commonwealth of Massachusetts, 2016). We also exclude buprenorphine formulations that are indicated for pain management rather than opioid use disorder (Wen et al., 2017).

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[10] SDUD includes the universe of prescriptions for which Medicaid, at least partially, financed the prescription in the Medicaid fee-for-service (FFS) program between 1992 and the second quarter of 2016. Beginning in March 2010, Medicaid managed care (MC) program prescriptions were included in the database. Therefore, we exclude years prior to 2011 as we have incomplete information on MC prescriptions. However, we have included 2010 in unreported analyses. We exclude 2016 as we only have data for quarters 1 and 2, however, we have included these data in unreported analyses. We have also excluded five states (AZ, HI, OH, RI, and VA) that display odd missing data patterns. Finally, we have analyzed the SDUD data at the quarterly level. These changes to the sample/data did not change our results in a meaningful way. More details and all results are available from the authors.

[11] In unreported analyses we explored whether Medicaid expansion predicted the probability of this missing data pattern and we found no evidence of any relationship. Details available on request from the authors.

[12] https://www.drugabuse.gov/publications/drugfacts/treatment-approaches-drug-addiction (accessed February 17th, 2017). We also consider branded versions of these generic drugs.

3.3 Medicaid expansion data

We rely on data from the Kaiser Family Foundation[13] and Sommers et al. (2013) to construct our Medicaid expansion variables. Table 1 reports expanding states and the associated expansion date. The majority of expanding states implemented their expansion on January 1st, 2014, coinciding with the availability of enhanced federal funding under the ACA. Six states (California, Connecticut, DC, New Jersey, Minnesota, and Washington) expanded under ACA provisions prior to 2014; we refer to these states as 'early expanding states'.[14] Two states expanded Medicaid later in 2014 (Michigan and New Hampshire). In addition, five states expanded in 2015 or 2016 (Alaska, Indiana, Louisiana, Montana, and Pennsylvania) and we refer to these states as 'late expanding states'. States that expanded Medicaid after December 31st, 2014 (December 31st, 2015) do not offer variation in our empirical models estimated in the TEDS (SDUD) because we only have data from this source through 2014 (2015).

The TEDS provides data annually and, although we aggregate the SDUD to the annual level in our analyses, these data are available at the quarter level. Thus we do not know the specific date on which an admission occurred or when a prescription was filled. For Medicaid expansions that occur within a year, we assign the expansion to a state based on the share of the year for which the expansion is in place. For example, Michigan expanded its Medicaid program on April 1st, 2014 (Table 1). We code the Michigan expansion variable as 0 in years 2010

[13] http://kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/?currentTimeframe=0 (accessed December 20th, 2016).

[14] Under the ACA statute, the federal government would provide 100% of the matching funds beginning in 2014 to states expanding Medicaid (this amount gradually decreases in subsequent years). The early expansion states received the full federal match in 2014, but for years prior to 2014 had to contribute their state's typical match rate. http://kff.org/medicaid/issue-brief/understanding-how-states-access-the-aca-enhanced-medicaid-match-rates/ (accessed March 4th, 2017).

through 2013, and 0.75 in 2014.[15] In the SDUD, prior to aggregating the data to the year-state level, we match expansions to the closest quarter.

3.4 Outcome variables

We consider several outcome variables in our analysis of the effect of state Medicaid expansions on SUD treatment utilization. These variables necessarily differ across our two datasets. First, we consider the number of admissions to specialty SUD treatment in the TEDS.[16] To construct the admissions measure, we convert the number of admissions to the rate per 100,000 persons in a state age 18 years and older using population data from the American Community Survey (ACS) (Flood et al., 2015) and the University of Kentucky Center for Poverty Research (2016).[17] Second, we consider the patient's source of insurance in the TEDS: private insurance, Medicaid insurance, other insurance (e.g., Medicare, Veteran's Health Administration), and uninsured. Third, regardless of what health insurance the patient may have, we consider the source of payment that is expected to finance the majority of a patient's treatment in the TEDS: private insurance, Medicaid insurance, self-payments, or states and localities (this measure also includes care provided for free and 'other' payment). This final payment captures safety net programs that are paid for outside of health insurance and patients paying out of pocket. Facilities can receive more than one type of payment; the TEDS defines the primary payer as whichever entity supports more than 50% of the cost of treatment.[18]

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[15] In unreported analyses, we follow Wherry and Miller (2016) and exclude DC, DE, MA, NY, and VT, the states that covered adults below 100% of the federal poverty level before the ACA, from the analysis sample. Results are not appreciably different from those reported in the manuscript and are available on request.

[16] The term 'admission' is used in the TEDS to broadly refer to the initiation of any new treatment in a particular setting. Admissions in the TEDS thus encompass services received in both inpatient and outpatient settings (where treatment is sometimes referred to as an 'encounter' rather than an 'admission').

[17] Specifically, we first construct the share of the population that is 18 years and older from the ACS and second we multiply this number by a state's population.

[18] Payer source is documented in the TEDS with the following item: 'Identifies the primary source of payment for this treatment episode. Guidelines: States operating under a split payment fee arrangement between multiple payment sources are to default to the payment source with the largest percentage. When payment percentages are

The TEDS is composed of a 'minimum dataset' that includes information that states are required to provide to SAMHSA and a 'supplementary dataset' that includes information that states voluntarily provide. Both the patient insurance status and payment source variables that we study are in the supplementary dataset and are therefore only available for a subset of states. Moreover, several states have substantial missing data in the insurance and payment variables. We retain only states that have less than 25% missing data in all years of the analysis period (2010-2014) to form our insurance and payment analysis samples (results are robust to alternative thresholds for missing data, e.g., 15%). After applying this exclusion criteria, we have 31 states in our insurance state sample and 26 states in our payment state sample. The specific states in these samples are listed in Appendix Table 2.

A concern with our analyses of these samples is that they may not reflect the experiences of the full set of U.S. states, thus calling to question the generalizability of our findings. To explore this issue, we compare demographics from the ACS for (i) admission sample states, (ii) insurance sample states, and (iii) payment sample states. Results are reported in Appendix Table 3 and suggest that, at least across these observable characteristics, the insurance and payment states samples are similar to states in admission states sample.[19]

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equal, the State can select either source.' This variable does not allow us to capture payment source with ideal accuracy. For example, we are unable to measure patients who use multiple payment sources to pay for treatment. We note our inability to accurately study the use of multiple payments as a limitation of this study.

[19] An additional, and perhaps more concerning issue from a bias standpoint, is that the Medicaid expansions that we study may have influenced whether a state reported insurance or payment information to SAMHSA and/or the degree of missingness in these variables. Either of these scenarios could lead to conditional-on-positive bias in our regression coefficient estimates (Angrist and Pischke, 2009). To explore this possibility, in unreported analyses we regress the probability that a state appears in our (i) insurance and (ii) payment variables on the Medicaid expansions we study.[19] Results, available on request, do not suggest that the Medicaid expansions affected these variables which provides some evidence that our analyses of the insurance and payment variables is not vulnerable to conditional-on-positive bias.

In terms of prescription medications used to treat SUDs in outpatient settings that are measured in the SDUD, we consider the number of prescriptions each year per 100,000 persons in a state among residents age 18 years and older.

3.5 Control variables

SUD treatment utilization is determined by myriad factors. Ideally, we would like to include variables in our regression models that are plausibly linked with both our outcomes and to the probability that a state expands its Medicaid program with the ACA, and therefore reduce omitted variable bias in our coefficient estimates. To this end, we merge state-level information from several sources into the TEDS and SDUD.

Specifically, we merge in annual state-level data on demographics from the ACS: average age, sex (male, female), race and Hispanic ethnicity (white, African American, other race, and Hispanic ethnicity), educational attainment (less than college, some college, and college graduate), marital status (married, divorced/separated/widowed, and never married), urbanicity (rural and urban residency shares), disabled,[20] and foreign born. We also merge in the annual unemployment rate from the Bureau of Labor Statistics Local Area Unemployment Database from the University of Kentucky Center for Poverty Research (2016).

We control for social policies that may reflect state attitudes toward the welfare of lower income populations (maximum monthly benefit for a family of four for the Supplemental Nutrition Assistance Program and Temporary Aid for Needy Families) and an indicator for whether the Governor is a Democrat (University of Kentucky Center for Poverty Research,

[20] More specifically, a cognitive, ambulatory, independent living, self-care, vision, and/or hearing disability. This variable proxies for a state's underlying health status.

2016).[21] Finally, we link state population 18 years and older (we do not control for population in the rate regressions as population is in the denominator of our outcome variables).

3.6 Empirical model

We follow the literature that investigates the effect of Medicaid expansions on health and healthcare outcomes (Simon et al., 2016, Ghosh et al., 2017, Wen et al., 2017), and apply a differences-in-differences regression model. Our empirical model is outlined in Equation (1):

(1) $$SUD_{st} = \alpha_0 + \alpha_1 Expand_{st} + \alpha_2' X_{st} + S_s + \tau_t + \varepsilon_{st}$$

SUD_{st} is an SUD treatment outcome in state *s* in time *t*. $Expand_{st}$ is an indicator for whether or not a state has expanded its Medicaid program. X_{st} is a vector of state level characteristics (see Section 3.5).[22] S_s and τ_t are vectors of state and year fixed effects. Inclusion of state fixed effects allows us to control for time-invariant state-level factors that are unobservable (to the econometrician) and implies that our regression models are identified off within state variation in Medicaid expansions. Year fixed effects control for secular trends in SUD utilization that affect the nation as a whole.[23] ε_{st} is the error term.

We estimate regression models using unweighted OLS (Solon et al., 2015). We cluster standard errors around the state (Bertrand et al., 2004). However, in unreported regressions we applied the wild cluster bootstrap (Cameron and Miller, 2015) in our insurance and payment regressions, as we have just 31 clusters in the insurance state sample and 26 clusters in the payment state sample. Results are comparable to our main analysis (and available on request).

3.7 Validity of the research design

[21] We treat the mayor of DC as the *de facto* Governor of this locality.
[22] Results are not appreciably different if we exclude the time-varying state-level controls.
[23] State and year fixed effects subsume the treatment and post indicators in a basic DD regression.

A necessary assumption for the DD model to recover causal estimates is that the treatment (i.e., states expanding Medicaid) and the comparison (i.e., states not expanding Medicaid) groups would follow the same trend in the post-treatment period, had the treatment states not been treated. However, this assumption is inherently untestable since the counterfactual condition is not observed for the treatment group. We instead attempt to provide suggestive evidence on this assumption. To this end, we proceed in two ways.

First, we examine unadjusted trends in the pre-treatment period in our outcome variables for the treatment and comparison groups. If we find that the outcomes appear to trend similarly in the pre-treatment period across these groups, such trends provide suggestive evidence that our TEDS and SDUD data satisfy the parallel trends assumption. Second, using the pre-treatment data only, we estimate regression models similar to Equation (1), except that we replace the DD variable with an interaction between the treatment group and a linear time trend (Antwi et al., 2013). This regression model is outlined in Equation (2):

$$(2) \qquad SUD_{st} = \gamma_0 + \gamma_1 Treat_s * Time_t + \gamma_2' X_{st} + S_s + \tau_t + \mu_{st}$$

If we cannot reject the null hypothesis that γ_1 is zero, then this finding provides further support that our datasets satisfy the parallel trends assumption. We exclude early expanding states (Table 1) from these analyses.

4. Results for specialty SUD treatment in the Treatment Episode Data Set

4.1 Summary statistics: TEDS

Table 2 reports summary statistics for expanding states in their pre-expansion years (Table 1) and non-expanding states 2010-2013. The mean number of annual admissions per 100,000 adults 18 years and older was 8.96 in expanding states and 7.04 in non-expanding states. Among patients receiving specialty SUD treatment in expanding states, 12.6% held private insurance, 19.1% Medicaid, 7.5% other insurance (e.g., Medicare), and 60.9% held no insurance (i.e., uninsured) at admission to treatment. For individuals in non-expanding states, the same percentages were 6.3%, 15.1%, 10.5%, and 68.1%, respectively.

In terms of the forms of primary payment patients receiving specialty SUD treatment used to finance care, 8.6% and 16.2% used private insurance and Medicaid insurance, while 19.1% self-paid and 56.1% relied on state and local governments, respectively. In non-expansion states the share with each source of payment was: 4.3% private insurance, 10.2% Medicaid insurance, 18.6% self-pay, and 66.9% state and local governments. Thus, as expected, both holding insurance and the use of insurance to pay for treatment was relatively uncommon among patients receiving treatment in TEDS-tracked facilities pre-Medicaid expansion.

State-level characteristics are also reported in Table 2. While obviously not identical, expanding and non-expanding states were broadly comparable across these characteristics pre-expansion. We nevertheless control for all of these factors in our regression models.

4.2 Validity of the research design: TEDS

Figures 1, 2, and 3 report trends in outcomes for treatment and comparison groups in admissions, insurance status, and payment source. Trends between the two groups of states appear to move in parallel in the pre-period, 2010-2013, for the majority of our outcomes; one exception to this pattern is the self-payment variable where the trend is more ambiguous. However, these figures reflect unadjusted trends in our outcome variables and our regression models – outlined in Equation (1) – control for numerous factors that may account for such differences in pre-treatment trends.

In terms of the post-period (for which we have just one year: 2014), we observe a steeper decline in the number of admissions to treatment in non-expanding states than expanding states.

In addition, we see larger increases in Medicaid insurance and Medicaid as a source of payment in expanding states in 2014 relative to non-expanding states. There were large declines in the share of patients with uninsured status in both groups of states (but a larger decrease in expansion states) and declines in state and localities as a source of payment for treatment.

Results from regression-based testing of the parallel trends assumption are reported in Tables 3A (admissions), 3B (insurance status), and 3C (payment source). We cannot reject the hypothesis that $\gamma_1 = 0$ in eight of the nine regressions we estimate. The exception to this pattern is the use of states and localities as the source of payment: we find that expanding states experienced a 2.4 percentage point (4.3%; $p<0.10$) increase in this payment form per year relative to non-expanding states. We return to this issue when interpreting our estimates generated in DD models. Overall, we note that the standard error estimates are rather large and limit our ability to rule out non-trivial violations of the parallel trends assumption. Reassuringly, the coefficient estimates are small in magnitude in all regressions and, as we report later in the manuscript, our findings are largely insensitive to the inclusion of state-specific time trends.

4.3 DD regression results: TEDS

Our core TEDS findings generated in the DD model outlined in Equation (1) are reported in Tables 4A (admissions), 4B (insurance status), and 4C (payment source).

We find no statistically significant evidence that Medicaid expansions led to changes in the number of admissions to specialty SUD treatment. Moreover, the coefficient estimate, which carries a positive sign, is small relative to the baseline mean.

When we look at patient insurance status among individuals in treatment, we find that, following a state expansion, the probability that a patient held Medicaid insurance coverage increased by 11.1 percentage points while the probability that a patient was uninsured declined by 11.3 percentage points (Table 4B). This pattern of results implies that virtually all the individuals gaining Medicaid post expansion were previously uninsured, and, while not definitive, suggests that extensive crowd-out did not occur (Cutler and Gruber, 1996).

The magnitude of these estimated effects is substantial: they imply a 58% increase in Medicaid coverage and a 19% decline in uninsurance relative to the pre-expansion mean for the expansion states. These substantial effects are in line with large-scale changes in private insurance coverage documented among young adults with SUDs under the ACA dependent coverage mandate (Saloner et al., 2017a). Moreover, our baseline proportion for Medicaid coverage is low which leads to large percent changes.

Our payment source findings largely mirror the insurance estimates (Table 4C). In particular, we find that following a state Medicaid expansion, patients in expanding states were 9.2 percentage points more likely to have Medicaid as a primary source of payment for treatment – a 57% increase over the pre-expansion baseline proportion in expanding states. Such patients were also 12.1 percentage points less likely to rely on states and localities to pay for treatment – a 22% decrease over the pre-expansion baseline proportion in expanding states. The similarity in magnitude (but opposing sign) of the coefficient estimates is in line with the hypothesis that facilities were able to offset treatment that had previously been financed by state and local grant funding with Medicaid payments. As in the insurance results, Medicaid payment was relatively low in the pre-expansion period, which leads to the large percent increase.

We find in Table 3C (regression-based parallel trends testing) that expanding states experienced an increase in the use of funding from states and localities to pay for specialty SUD treatment in the pre-expansion period relative to non-expanding states (i.e., a positive beta coefficient estimate on the interaction between the treatment group and a linear time trend). Our

DD estimates suggest that expanding states also experienced a decrease in this source of payment post-expansion relative to non-expanding states. Combining these two findings suggests that our DD estimates may in fact *understate* the effects of the Medicaid expansions on the use of states and localities to pay for treatment.

5. Results for prescription medication use in the State Drug Utilization Database

5.1 Summary statistics: SDUD

Table 5 reports summary statistics for the pre-expansion period for expanding states and 2010-2013 for non-expanding states using the SDUD data. The mean annual prescription rate for SUD medications financed by Medicaid per 100,000 adults 18 years and older was 3,016 in expanding states pre-expansion and 1,656 in the non-expanding states 2011-2013.

5.2 Validity of the research design: SDUD

Figure 4 documents similar patterns in prescription outcomes over the 2011 to 2013 period for expanding and non-expanding states, followed by an increase in prescription rates in expanding states relative to non-expanding states 2014 to 2015.

Table 6 reports regression-based parallel trends testing of the SDUD. Specifically, we estimate Equation (2) in these data. We are most interested in the coefficient estimate on the interaction between the treatment group indicator and the linear time trend (γ_1). We cannot reject the null hypothesis ($\gamma_1 = 0$). However, as is the case in TEDS, our standard errors are somewhat large. To account for our inability to precisely estimate γ_1, we explore the robustness of our estimates to the inclusion of state-specific time trends later in the paper.

5.3 DD regression results: SDUD

Our DD estimates for the effect of the ACA Medicaid expansions on prescriptions for medications used to treat SUDs are reported in Table 6. We find that expanding states experienced an increase of 994 prescriptions per 100,000 adults 18 years and older per year post expansion, relative to non-expanding states. This estimate represents a 33% increase over the pre-expansion mean in expanding states.[24]

6. Extensions and robustness checks

This section presents extensions to the main analyses and summarizes several robustness checks that we conducted to affirm the stability of our findings.

6.1 The effect of ACA-related Medicaid expansions on fatal alcohol poisonings and drug-related overdoses

We have explored the effect of ACA-related Medicaid expansions on SUD treatment use. Since these expansions are ultimately aimed at improving health, understanding whether they affected key health outcomes is important. Thus, we next estimate the effect of Medicaid expansions on proxies for harmful substance use within the population: fatal alcohol poisonings and drug-related overdoses.

We examine data from the National Vital Statistics Mortality Files (NVSM) between 2010 and 2015. NVSM tracks all-cause mortality in the U.S. and therefore provides us with the universe of deaths classified as alcohol poisoning and drug-related overdose. We construct the number of fatal alcohol poisonings and drug-related overdoses using ICD-10 codes.[25] We use data on fatal alcohol poisonings and drug-related overdoses among non-elderly adults: 20 to 64

[24] SDUD contains information on the total reimbursement, Medicaid, and non-Medicaid reimbursement for each prescription. This information allows us to explore whether Medicaid or patients (through cost-sharing) are responsible for financing use of these medications. In unreported analyses we regressed total, Medicaid, and non-Medicaid reimbursements on the expansion indicator using Equation (1). Broadly, total reimbursement increased among expansion states relative to non-expansion states in the post-expansion period, and Medicaid financed the vast majority of the prescriptions (the coefficient estimates in the total and Medicaid reimbursement regressions are very similar in magnitude while the coefficient estimate in the non-Medicaid regression carry a negative sign). This finding is perhaps not surprising as cost-sharing is low in the Medicaid program, but nonetheless the finding implies that Medicaid patients are not bearing the full financial burden of increased utilization of medications used to treat SUDs. We note, however, that these findings are generally imprecisely estimated.

[25]The specific ICD-10 codes are: X40–X45, X60–X65, and Y10–Y14.

years (the public use NVSM are available in five year age intervals only, thus preventing us from including poisoning and overdose deaths among 19 years olds). We convert deaths to the rate per 100,000 adults ages 18 years and older. Comparable to the TEDS, the NVSM data are annual and thus we apply the same matching procedure to link the Medicaid expansion dates to the NVSM data as we applied in the TEDS (see Section 3.3).

We estimate Equation (1) in the NVSM data. Results are reported in Appendix Table 4. We also report regression-based parallel trends testing, which supports the hypothesis that the NVSM data are able to satisfy the parallel trends assumption. Our findings do not suggest that the Medicaid expansions we study led to changes in fatal alcohol poisonings and drug-related overdoses: the regression coefficient estimate is small relative to the baseline mean and is not statistically different from zero. However, poisoning and overdose deaths are arguably a blunt measure of substance use. Future studies, evaluating measures of harmful substance use that have a higher prevalence and/or longer time series, could re-evaluate this question.

6.2 Policy endogeneity: TEDS and SDUD

A general concern in analyses of health and healthcare policies, such as the Medicaid expansions we investigate here, is that state legislatures concerned with deteriorating health or underutilization of healthcare services within the population may implement policies to address these concerning trends. In such a scenario, outcomes may lead to changes in policies rather than policies leading to changes in outcomes (i.e., a form of reverse causality at the state-level).

To explore this possibility, we estimate an event study (Autor, 2003). More specifically, we estimate a variant of Equation (1) in which we include a series of policy leads in the regression model (we are unable to include policy lags in the TEDS, as is standard in an event study, as the TEDS do not currently extend past 2014). We exclude early expanding states from this analysis. Our leads and lags consist of interactions between year indicators for 2010-2012 and 2014, and an indicator for expanding states (i.e., those states that expanded in 2014). In the event study, 2013 is the omitted year. If we find evidence that the leads are statistically different from zero, this pattern in the data might suggest that our data is subject to policy endogeneity. However, after we condition for such endogeneity through the inclusion of policy leads, we can minimize concerns regarding reverse causality bias and recover causal estimates for the lags.

Results generated in the event study are reported in Appendix Table 5A (admissions), 5B (insurance status), and 5C (payment source). Overall, we find little evidence of policy endogeneity: the coefficient estimates on the leads are generally statistically indistinguishable from zero and *F*-tests of lead joint significance lead to the same conclusion. Moreover, the coefficient estimates on the interaction between the treatment group and the year 2014 (which corresponds to our DD estimate in the main regression models) are not appreciably different from those reported in Tables 4A (admissions), 4B (insurance status), and 4C (payment source).

We also conduct a similar event study for prescription medications in the SDUD data (Table 5D). We are able to include an additional policy lag (2015) in our analysis of the SDUD. Comparable to the TEDS, we find no evidence of policy endogeneity (coefficient estimates on the leads are not statistically distinguishable from zero, *F*-tests of joint significance of the leads provide comparable results). However, our analysis of the policy lags suggests that the effects of the Medicaid expansions may increase over time: more specifically, the coefficient on the 2015 lag is larger in magnitude than the 2014 lag.

6.3 Controlling for between-state differences

Although we cannot reject the null hypothesis that the treatment and comparison groups trended similarly in the pre-treatment period, the standard errors on the interaction between the treatment group and the linear time trend in Equation (2) are large and prevent us from ruling out non-trivial differences in pre-treatment trends. Indeed, we find statistically significant evidence of different pre-treatment trends for one outcome (the use of funds from states and localities to pay for treatment) in expanding and non-expanding states.

To explore the extent to which our findings may be driven by differences in pre-treatment trends between the treatment and comparison groups, we re-estimate Equation (1) including state-specific linear time trends. Including these state trends allows each state to follow a separate, albeit linear, trend in the outcome variables and thus allows us to control for trend differences. Results from these analyses are reported in Tables 6A (admissions), 6B (insurance status), 6C (payment source), and 6D (prescriptions). Overall, our findings are broadly robust to the inclusion of these trends. However, as these models are data intensive and we have a relatively small amount of variation in the data (Table 1), we not surprisingly find that our results are less precisely estimated. For example, the coefficient estimate in the use of Medicaid to pay for treatment is no longer precise. Reassuringly, the coefficients are quite stable in terms of sign and magnitude (although somewhat smaller in some regressions) vis-à-vis our core findings (i.e., DD results reported in Tables 4A, 4B, 4C, and 6).

6.4 Population weighting

Our regressions are unweighted. However, there is some controversy within the economics literature as to whether weights should be applied in economic analyses seeking to estimate causal effects (Angrist and Pischke, 2009). To explore the robustness of our findings, we re-estimate our regressions using population weighting (i.e., the state population ages 18+ serve as our weights). Results from these analyses are reported in Appendix Table 7A (admissions), 7B (insurance status), 7C (payment source), and 7D (prescriptions).

Our findings are broadly robust to weighting. However, we also find that holding private insurance and using private insurance to pay for treatment increased in expanding states relative to non-expanding states in the post-expansion period. We are uncertain why more individuals in expansion states would also use private insurance after expansion – one potential explanation is that Medicaid expansion could induce greater acceptance of insurance overall, leading to a positive spillover on privately insured individuals (Finkelstein, 2007, Glied and Zivin, 2002).[26]

6.5 Additional extensions and robustness checks

We have conducted several other extensions and robustness checks that are available on request from the authors. We explore whether there are changes in the composition of patients receiving treatment in TEDS-tracked facilities (which is suggested by the changes of insurance status and payment forms among patients receiving treatment). Compositional changes are important to test because, among other things, they can provide some indication of either changes in provider behavior, e.g., differential acceptance of specific populations (Sloan et al., 1978), or choices patients may make regarding where to seek treatment.[27] We construct indicator variables for sex, age, primary substance targeted for treatment, race/ethnicity, prior treatment, and referral source. We find no evidence that composition of patients, across these observable dimensions, changed in expansion states relative to non-expansion states.

Patients gaining access to Medicaid may be able access specialty treatment in settings that may not have been available when they were uninsured. For example, an uninsured individual seeking SUD treatment may find it cost-prohibitive to access intensive outpatient or residential treatment and may thus rely on less expensive non-intensive treatment or detoxification. To explore this issue, we estimated a series of regressions in which we model

[26] The coefficient estimates, while imprecise, in the unweighted regressions also carried a positive sign.
[27] Our data will not allow us to shed light on whether this phenomenon is driven by providers or patients, however.

specialty SUD treatment setting – detoxification, non-intensive outpatient, intensive outpatient, and inpatient – on Medicaid expansions in Equation (1) using TEDS. We find no evidence that these expansions altered the setting in which patients receive care.

We aggregate our insurance and payment samples to the state-level in the TEDS. In unreported analyses, we have disaggregated these variables to the patient level. Overall, our analyses are not appreciably different to this alternative specification.

7. Discussion

In this study we investigated the early effects of recent state-level Medicaid expansions that occurred under the 2010 Affordable Care Act on substance use disorder (SUD) treatment utilization. By 2017, 32 states (including DC) expanded income eligibility for Medicaid up to 138% of the federal poverty level, with the majority of states expanding in January 2014. These expansions targeted populations that previously had little access to public insurance in the United States: low-income, non-elderly adults. Moreover, a generous set of SUD services was a required benefit under these expansions (Beronio et al., 2014). These services may hold particular value for the group of individuals that gained insurance coverage through these expansions as such individuals have elevated SUD prevalence (Busch et al., 2013).

Our findings suggest that there was no change in admissions to specialty SUD treatment in expanding states relative to non-expanding states, but our data set only allows us to explore effects through 2014. Changes in use of SUD services may also take time because of existing capacity constraints within the SUD treatment delivery system (Carr et al., 2008): meaning that providers may initially lack the space to allow additional patients into treatment (Saloner, 2017).

We find that the ACA-related Medicaid expansions substantially changed the insurance status of treated populations and the financial burden of treatment. Specifically, we find that

Medicaid as a source of insurance increased 58% (offset mainly by a reduction in the uninsured) and Medicaid as a source of payment increased 57% (offset mainly by reduced spending by states and localities which captures charity care). The reduced spending by states and localities on safety net treatment can also increase resources available within constrained public health budgets to address other public health priorities. For patients, increasing payment by Medicaid can also reduce out-of-pocket spending burden – i.e., a potential financial relief. Recent research on the ACA Medicaid expansion finds that expansion improved financial wellbeing and reduced debt in expansion states (Hu et al., 2016), which is in line with our finding for payment source.

Our TEDS findings can also be compared to other recent studies that have examined how the coverage and sources of payment changed after Medicaid expansion in other low-income and safety net settings. Among individuals 19-64 with family incomes less than 138% of the federal poverty level, post-expansion Medicaid insurance increased by 10.2 percentage points (34) while uninsurance declined by 7.4 percentage points (22%) in expanding states relative to non-expanding states (Wherry and Miller, 2016). The share of Medicaid insured patients treated at community health centers increased by 11.8 percentage points (30%) in 2014 in expansion states compared to non-expansion states (Cole et al., 2017). Moreover, inpatient hospital discharges covered by Medicaid increased by 6.2 percentage points (18%) in expansion states (Nikpay et al., 2016). Our estimated changes in insurance coverage and payment in absolute amounts are in line with these changes, but are somewhat larger in relative terms (because of the lower baseline role of Medicaid insurance and payment within SUD treatment).

We find that the volume of prescriptions for medications approved by the Food and Drug Administration to treat SUDs reimbursed by Medicaid increased 33% in expanding states after the expansion relative to non-expanding states. This increase is in line with a recent study by

Wen et al. (2017) that also used the SDUD data, but focused exclusively on buprenorphine treatment. These authors find that, post-expansion, Medicaid-financed prescriptions for this medication increased 70% in expanding states relative to non-expanding states.

Our study is not without limitations. First, because most of the Medicaid expansions occurred between 2014 and 2016, we and other studies in the literature, have little post-expansion data for all but the early expanding states. Thus our findings represent the early effects for most states. Second, our insurance and payment analysis of the Treatment Episode Dataset (TEDS) relies on just over half the states, which may limit the generalizability of our findings. Third, while we study two important forms of SUD treatment (specialty SUD treatment and prescription medications designed to treat SUDs in outpatient settings), we do not capture all dimensions of SUD treatment.

The findings reported in this study are timely and important. Legislation to repeal and replace the ACA was introduced in the U.S. House of Representatives in March 2017, but was withdrawn before a full vote. This proposal was predicted to lead to large-scale insurance losses.[28] Whether or not further legislation to repeal Medicaid expansion is introduced, the Trump Administration is likely to alter ACA through its regulatory authority (e.g., federal waivers allowing states to deviate from statutory requirements).

In conclusion, our study provides a starting point for assessing the impact of Medicaid expansion under the ACA on SUD treatment and outcomes. These findings may be useful to state and federal policymakers considering changes that might modify the current structure of the ACA, and also speaks to the relevance of Medicaid in state and local budgets—especially since SUD services are a major expenditure for states and localities. Further evaluation can indicate

[28] https://www.cbo.gov/sites/default/files/115th-congress-2017-2018/costestimate/americanhealthcareact.pdf (accessed March 21st, 2017).

whether expanded Medicaid coverage and funding had positive impacts on the health and wellbeing of populations in SUD treatment, and on the communities in which they reside.

Table 1. State Affordable Care Act (2010) related Medicaid expansions: 2010-2017

State	Expansion date
Early expanding states	
California	7/1/2011
Connecticut	4/1/2010
District of Columbia	7/1/2010
Minnesota	3/1/2011
New Jersey	4/14/2011
Washington	1/3/2011
States expending in 2014	
Arizona	1/1/2014
Arkansas	1/1/2014
Colorado	1/1/2014
Delaware	1/1/2014
Hawaii	1/1/2014
Illinois	1/1/2014
Iowa	1/1/2014
Kentucky	1/1/2014
Maryland	1/1/2014
Massachusetts	1/1/2014
Michigan	4/1/2014
Nevada	1/1/2014
New Hampshire	8/15/2014
New Mexico	1/1/2014
New York	1/1/2014
North Dakota	1/1/2014
Ohio	1/1/2014
Oregon	1/1/2014
Rhode Island	1/1/2014
Vermont	1/1/2014
West Virginia	1/1/2014
Late expanding states	
Alaska	9/1/2015
Indiana	2/1/2015
Montana	1/1/2016
Louisiana	7/1/2016
Pennsylvania	1/1/2015

Notes: Medicaid expansion dates derived from Kaiser Family Foundation and Sommers et al (2013).

Table 2. Summary statistics for expansion and non-expansion states: TEDS 2010-2013

Sample:	Expansion states	Non-expansion states
Admissions		
Admissions per 100,000	8.962	7.039
*Insurance status (N=53 in expansion states, N=77 in non-expansion states)**		
Private insurance	0.126	0.0631
Medicaid insurance	0.191	0.151
Other insurance	0.0746	0.105
Uninsured	0.609	0.681
*Payment source(N=49 in expansion states, N=54 in non-expansion states)***		
Private insurance	0.0863	0.0429
Medicaid insurance	0.162	0.102
Self-pay	0.191	0.186
State and local government	0.561	0.669
State characteristics		
Age	38.32	37.40
Female	0.507	0.505
Male	0.493	0.495
White	0.700	0.727
African American	0.0809	0.118
Other race	0.0952	0.0666
Hispanic	0.124	0.0884
Foreign born	0.114	0.0754
Less high school	0.309	0.325
High school	0.293	0.297
Some college	0.192	0.194
College degree	0.206	0.184
Married	0.395	0.400
Divorced/separated/widowed	0.195	0.194
Never married	0.447	0.442
Urban	0.656	0.571
Rural	0.344	0.429
Disabled	0.131	0.135
Family income ($)	77602	71137
Unemployment rate	7.917	7.396
Poverty rate	13.88	14.47
Maximum monthly SNAP benefit for a family of 4 ($)	717.6	704.2
Maximum monthly TANF benefit for a family of 4 ($)	596.4	457.7
Democrat Governor	0.621	0.198
Population	4206065	4541497
N	87	91

Notes: The pre-treatment period for early adopting states includes the years between 2010 and the expanding year.
*Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY.
**Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT.

Table 3A. Parallel trends testing for admissions: TEDS 2010-2013

Outcome:	Admissions per 100,000
Pre-expansion mean in the expansion state group	8.962
Treat*time	-0.047
	(0.830)
N	174

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Table 3B. Parallel trends testing for insurance status: TEDS 2010-2013

Outcome:	Private	Medicaid	Other insurance	Uninsured
Pre-expansion proportion in the expansion state group	0.126	0.191	0.075	0.609
Treat*time	0.002	0.005	-0.001	-0.006
	(0.655)	(0.509)	(0.774)	(0.615)
N	114	114	114	114

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Standard errors are clustered at the state level and are reported in parentheses. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Table 3C. Parallel trends testing for payment source: TEDS 2010-2013

Outcome:	Private	Medicaid	Self-pay	States and localities
Pre-expansion proportion in the expansion state group	0.0863	0.162	0.191	0.561
Treat*time	-0.001	-0.006	-0.017	0.024*
	(0.805)	(0.105)	(0.213)	(0.067)
N	91	91	91	91

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Standard errors are clustered at the state level and are reported in parentheses. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Table 4A. Effect of ACA Medicaid expansions on admissions: TEDS 2010-2014

Outcome:	**Admissions per 100,000**
Pre-expansion mean in the expansion state group	8.962
DD	0.018
	(0.969)
N	247

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Table 4B. Effect of ACA Medicaid expansions on insurance status: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Other insurance**	**Uninsured**
Pre-expansion proportion in the expansion state group	0.126	0.191	0.075	0.609
DD	0.036	0.111**	-0.034	-0.113**
	(0.221)	(0.039)	(0.357)	(0.044)
N	151	151	151	151

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Table 4C. Effect of ACA Medicaid expansions on payment source: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Self-pay**	**States and localities**
Pre-expansion proportion in the expansion state group	0.0863	0.162	0.191	0.561
DD	0.019	0.092**	0.009	-0.121**
	(0.136)	(0.026)	(0.781)	(0.041)
N	123	123	123	123

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Table 5. Summary statistics for expansion and non-expansion states in the pre-expansion period: SDUD 2011-2013

Sample:	Expansion states	Non-expansion states
Prescriptions		
Prescriptions per 100,000	3016.3	1656.0
State characteristics		
Age	38.32	37.56
Female	0.505	0.507
Male	0.495	0.493
White	0.710	0.719
African American	0.0802	0.133
Other race	0.0985	0.0577
Hispanic	0.111	0.0903
Foreign born	0.104	0.0745
Less high school	0.307	0.324
High school	0.299	0.295
Some college	0.192	0.196
College degree	0.203	0.184
Married	0.394	0.399
Divorced/separated/widowed	0.196	0.196
Never married	0.449	0.442
Urban	0.649	0.564
Rural	0.351	0.436
Disabled	0.133	0.137
Family income ($)	78194	70618
Unemployment rate	0.0843	0.0822
Poverty rate	13.85	14.85
Maximum monthly SNAP benefit for a family of 4 ($)	719.7	698.9
Maximum monthly TANF benefit for a family of 4 ($)	598.9	422.8
Democrat Governor	0.520	0.127
N	75	63

Notes: The pre-treatment period for early adopting states includes the years between 2011 and the expanding year.

Table 6. Effect of ACA Medicaid expansions on prescription outcomes per 100,000: SDUD 2011-2015

Coefficient estimate:	Parallel trends (Treat*time+)	DD
Pre-expansion mean in the expansion state group	3016.3	3016.3
Expansion	144.179	994.207**
	(0.122)	(0.035)
N	135	255

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses.
+Early expanding states dropped from the analysis sample.
***;*=statistically different from zero at the 1%;5%;10% level

Appendix Table 1. States missing from TEDS by year 2010-2014

Year	States
2010	DC; MS
2011	MS
2012	MS; PA; WY
2013	PA
2014	SC

Appendix Table 2. TEDS states by sample

Year	States
Insurance sample	AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY
Payment sample	AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT

Notes: All states appear in the admissions sample.

Appendix Table 3. TEDS sample characteristics by sample

Sample:	Admissions states	Insurance states	Payment states
Age	37.94	37.78	37.72
Female	0.506	0.506	0.504
Male	0.494	0.494	0.496
Hispanic	0.112	0.0947	0.0973
White	0.701	0.712	0.722
African American	0.104	0.106	0.0882
Other race	0.0830	0.0873	0.0929
Foreign born	0.103	0.0929	0.0923
Less high school	0.313	0.311	0.311
High school	0.292	0.293	0.291
Some college	0.192	0.192	0.194
College degree	0.203	0.204	0.204
Married	0.394	0.396	0.397
Divorced/separated/widowed	0.194	0.192	0.190
Never married	0.450	0.449	0.450
Urban	0.641	0.612	0.590
Rural	0.359	0.388	0.410
Disabled	0.132	0.131	0.130
Family income ($)	76652	77357	76705
Unemployment rate	7.334	7.026	6.885
Poverty rate	14.06	13.67	13.47
Maximum monthly SNAP benefit for a family of 4 ($)	695.9	703.2	706.9
Maximum monthly TANF benefit for a family of 4 ($)	532.5	528.4	540.1
Democratic Governor	0.441	0.457	0.423
Population	4731487	3509170	3132278
N	247	151	123

Notes: Data are aggregated to the state-year level. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT.

Appendix Table 4. Effect of ACA Medicaid expansions on alcohol poisoning and drug-related overdose deaths: NVSM 2010-2015

Coefficient estimate:	Parallel trends (Treat*time+)	DD
Pre-expansion mean in the expansion state group	19.79	19.79
Expansion	0.235	0.779
	(0.477)	(0.392)
N	180	306

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses.
+Early expanding states dropped from the analysis sample.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 5A. Event study for admissions: TEDS 2010-2014

Outcome:	**Admissions per 100,000**
Pre-expansion mean in the expansion state group	8.962
2010*treat	0.210
	(0.717)
2011*treat	0.087
	(0.869)
2012*treat	0.060
	(0.827)
2014*treat	0.380
	(0.356)
F-test of joint significance of policy leads (*p*-value)	0.9797
N	218

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses. The omitted year is 2013. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 5B. Event study for insurance status: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Other insurance**	**Uninsured**
Pre-expansion proportion in the expansion state group	0.126	0.191	0.075	0.609
2010*treat	-0.009	-0.023	0.022	0.010
	(0.631)	(0.421)	(0.396)	(0.811)
2011*treat	-0.008	-0.018	0.031	-0.006
	(0.615)	(0.363)	(0.170)	(0.870)
2012*treat	-0.001	-0.011	0.014	-0.002
	(0.929)	(0.429)	(0.397)	(0.942)
2014*treat	0.024	0.110**	-0.026	-0.109*
	(0.310)	(0.031)	(0.501)	(0.053)
F-test of joint significance of policy leads (*p*-value)	0.6054	0.7903	0.5227	0.9027
N	142	142	142	142

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Standard errors are clustered at the state level and are reported in parentheses. The omitted year is 2013. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 5C. Event study for payment source: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Self-pay**	**States and localities**
Pre-expansion proportion in the expansion state group	0.0863	0.162	0.191	0.561
2010*treat	-0.005	-0.006	0.042	-0.032
	(0.717)	(0.772)	(0.285)	(0.566)
2011*treat	-0.003	-0.017	0.031	-0.010
	(0.799)	(0.416)	(0.420)	(0.847)
2012*treat	-0.002	-0.009	-0.002	0.013
	(0.866)	(0.547)	(0.950)	(0.706)
2014*treat	0.016	0.107**	-0.003	-0.121*
	(0.232)	(0.011)	(0.948)	(0.097)
F-test of joint significance of policy leads (*p*-value)	0.8898	0.8082	0.7341	0.6264
N	114	114	114	114

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Standard errors are clustered at the state level and are reported in parentheses. The omitted year is 2013. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 5D. Event study for prescriptions per 100,000: SDUD 2010-2015

Outcome:	**Prescriptions**
Pre-expansion mean in the expansion state group	3016.3
2011*treat	-168.037
	(0.634)
2012*treat	-102.516
	(0.628)
2014*treat	729.121*
	(0.078)
2015*treat	1614.665**
	(0.015)
F-test of joint significance of policy leads (*p*-value)	0.8652
N	225

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and period fixed effects. Standard errors are clustered at the state level and are reported in parentheses. The omitted year is 2013. Early expanding states excluded from the sample.
***;**;*=statistically different from zero at the 1%;5%;10% level.

Appendix 6A. Effect of ACA Medicaid expansions on admissions including state-specific linear time trends: TEDS 2010-2014

Outcome:	**Admissions per 100,000**
Pre-expansion mean in the expansion state group	8.962
DD	0.304
	(0.491)
N	247

Notes: All models estimated with OLS and control for state demographics, state-specific linear time trends, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses. ***;*=statistically different from zero at the 1%;5%;10% level.

Appendix 6B. Effect of ACA Medicaid expansions on insurance status including state-specific linear time trends: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Other insurance**	**Uninsured**
Pre-expansion proportion in the expansion state group	0.126	0.191	0.075	0.609
DD	0.032	0.083	-0.012	-0.103*
	(0.322)	(0.175)	(0.739)	(0.076)
N	151	151	151	151

Notes: All models estimated with OLS and control for state demographics, state-specific linear time trends, state fixed effects, and year fixed effects. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 6C. Effect of ACA Medicaid expansions on payment source including state-specific linear time trends: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Self-pay**	**States and localities**
Pre-expansion proportion in the expansion state group	0.0863	0.162	0.191	0.561
DD	0.029	0.078*	0.021	-0.129**
	(0.120)	(0.068)	(0.371)	(0.021)
N	123	123	123	123

Notes: All models estimated with OLS and control for state demographics, state-specific linear time trends, state fixed effects, and year fixed effects. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 6D. Effect of ACA Medicaid expansions on prescription outcomes per 100,000 including state-specific linear time trends: SDUD 2011-2015

Outcome:	**Prescriptions per 100,000**
Pre-expansion mean in the expansion state group	3016.3
DD	450.293*
	(0.083)
N	255

Notes: All models estimated with OLS and control for state demographics, state-specific linear time trends, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses. ***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 7A. Effect of ACA Medicaid expansions on admissions using population weights: TEDS 2010-2014

Outcome:	**Admissions per 100,000**
Pre-expansion mean in the expansion state group	9.999
DD	-0.368
	(0.317)
N	247

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 7B. Effect of ACA Medicaid expansions on insurance status using population weights: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Other insurance**	**Uninsured**
Pre-expansion proportion in the expansion state group	0.126	0.224	0.071	0.579
DD	0.064**	0.099**	-0.044	-0.119***
	(0.047)	(0.042)	(0.256)	(0.010)
N	151	151	151	151

Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 7C. Effect of ACA Medicaid expansions on payment source using population weights: TEDS 2010-2014

Outcome:	**Private**	**Medicaid**	**Self-pay**	**States and localities**
Pre-expansion proportion in the expansion state group	0.0610	0.141	0.186	0.612
DD	0.037**	0.116***	0.015	-0.167***
	(0.010)	(0.009)	(0.507)	(0.001)
N	123	123	123	123

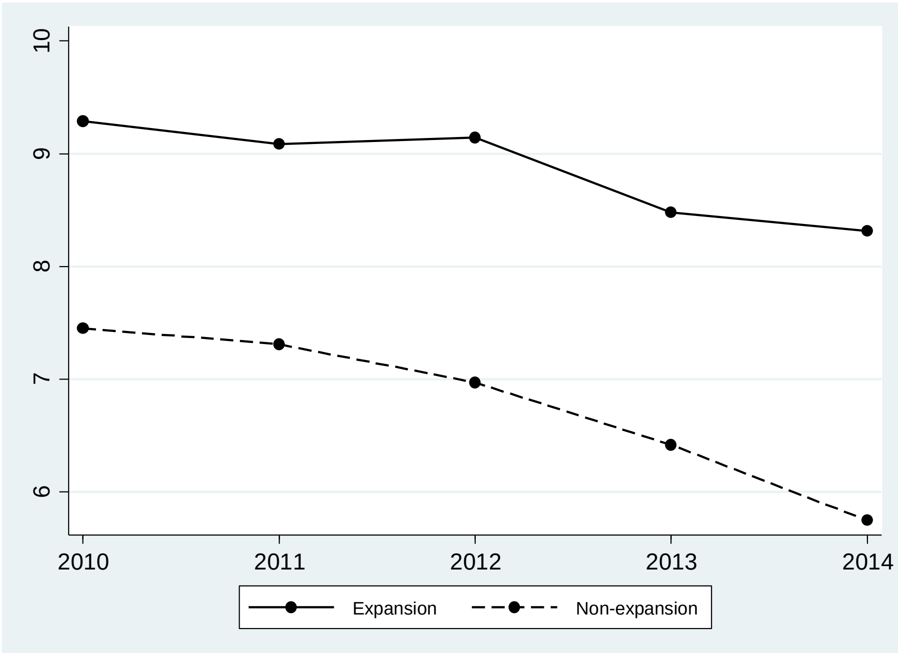
Notes: All models estimated with OLS and control for state demographics, state fixed effects, and year fixed effects. Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Appendix Table 7D. Effect of ACA Medicaid expansions on prescription outcomes per 100,000 using population weights: SDUD 2011-2015

Outcome:	**Prescriptions per 100,000**
Pre-expansion mean in the expansion state group	2616.6
DD	573.852*
	(0.062)
N	255

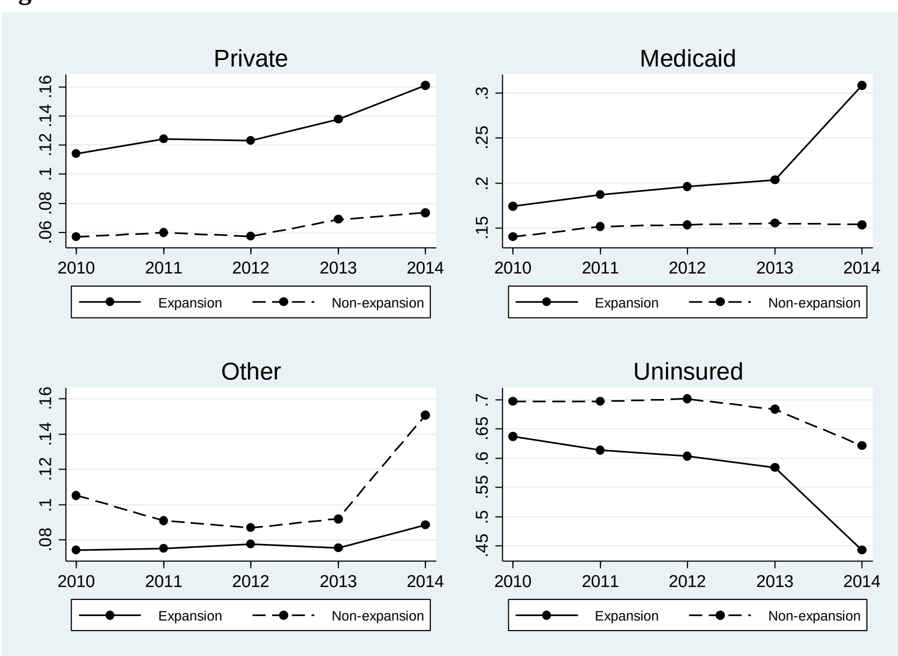
Notes: All models estimated with OLS and control for state demographics, state-specific linear time trends, state fixed effects, and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses.
***;*=statistically different from zero at the 1%;5%;10% level.

Figure 1. Trends in admissions per 100,000: TEDS 2010-2014



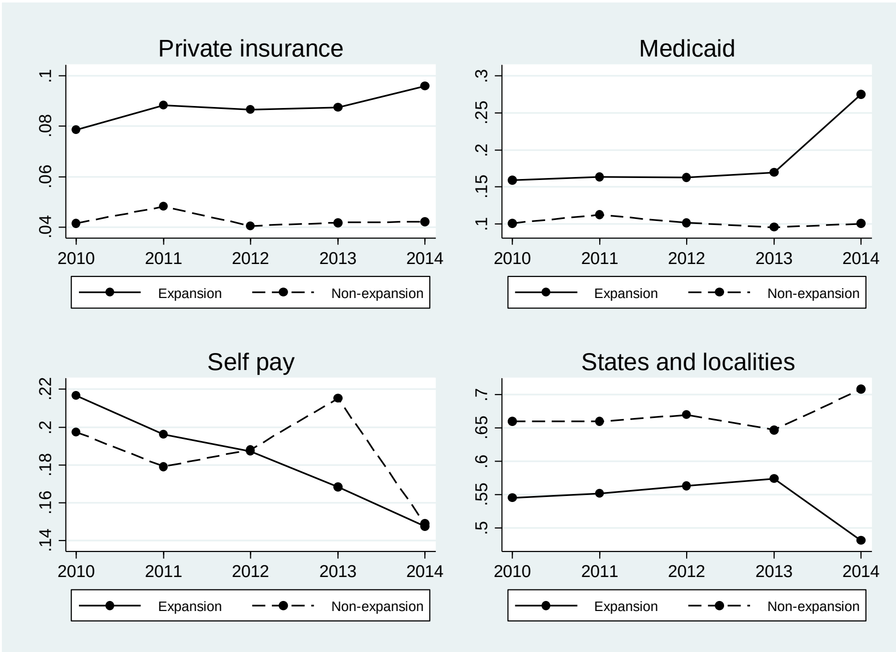
Notes: Outcome is admissions per 100,000. Early expanding states excluded from the sample.

Figure 2. Trends in insurance status: TEDS 2010-2014



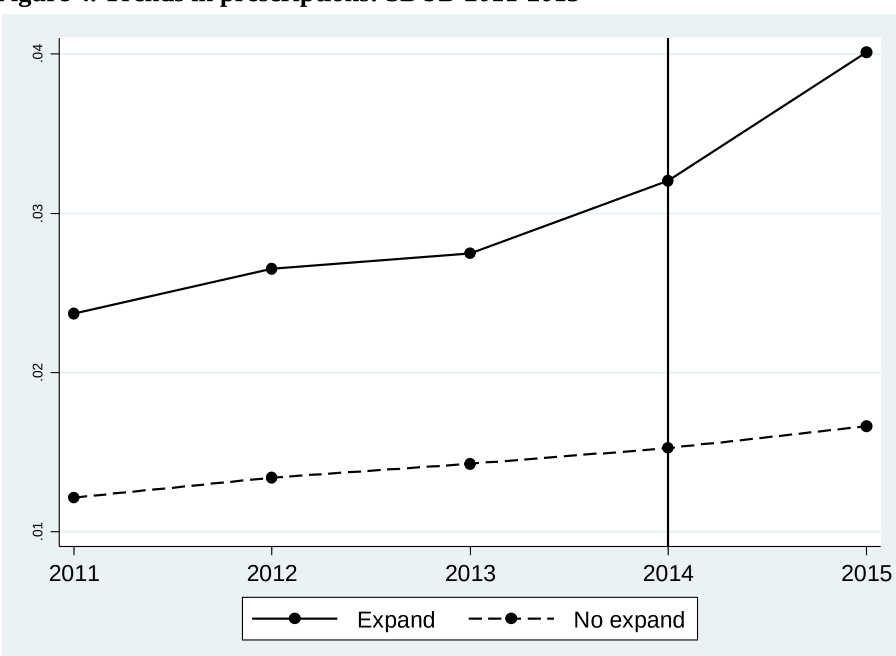
Notes: Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, LA, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, UT, and WY. Early expanding states excluded from the sample.

Figure 3. Trends in payment source: TEDS 2010-2014



Notes: Payment source state sample includes the following states: AK, AR, CO, DC, DE, HI, IA, ID, KS, KY, MO, MS, MT, ND, NE, NH, NJ, NV, OH, PA, RI, SC, SD, TX, UT, and VT. Early expanding states excluded from the sample.

Figure 4. Trends in prescriptions: SDUD 2011-2015



Notes: Outcome is prescriptions per 100,000. Early expanding states excluded from the sample.

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