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ABSTRACT

Even among commercially-insured individuals, opioid use disorder (OUD) is undertreated in the U.S.: nearly half receive no treatment within 6 months of a new diagnosis. Using a difference-in-differences specification exploiting the extension of insurance parity requirements for substance disorder treatment to small group enrollees in 2014, we find that parity increases utilization of residential treatment but decreases utilization of agonist medications, the standard of care. We find direct interventions to increase access to medication may be more promising: increases in the county-level share of physicians able to prescribe agonists are associated with substitution toward medication-assisted treatment.

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A data appendix is available at http://www.nber.org/data-appendix/w29001

1 Introduction

Since the 1996 introduction of OxyContin, the extended-release oxycodone preparation marketed to treat acute or chronic pain, the rate of opioid dependence and abuse has skyrocketed in the U.S.[1] Deaths from overdoses involving opioids have climbed annually, rising from just over 10,000 per year in 2000 to 49,860 in 2019, far exceeding deaths attributed to car accidents in recent years (CDC/NCHS, 2018). The growth in fatal overdoses since 2013 has been particularly steep, owing in part to increasing consumption of synthetic opioids such as fentanyl, which is 50-100 times more potent than morphine.[2]

To date, most policy interventions and academic studies have focused on curbing prescriptions for opioids and physician prescribing behavior (e.g. Schnell, 2017; Alpert et al., 2020). There is evidence these efforts have reduced both the volume of prescriptions as well as the quantities prescribed (Bao et al., 2016; Buchmueller and Carey, 2018; Sacks et al., 2021). Given that an estimated 8-12 percent of patients prescribed opioids for chronic pain have historically developed an opioid use disorder (OUD) (Cicero et al., 2014), these efforts should lead to a reduction in OUD prevalence. However, an estimated 1.6 million Americans already suffer from OUD, and there is a pressing need for additional research on how to increase access to, and utilization of, treatment—particularly medication-assisted treatment, for which there is the most robust clinical support.

This study helps to address this gap. Using data from a large commercial claims database between 2008-2017, we study treatment utilization, clinical outcomes, and spending among a sample of individuals newly diagnosed with OUD. Just 53 percent of commercially-insured individuals newly diagnosed with OUD received medication within six months of their diagnosis, and this share actually declined over our sample period (Shen et al., 2020).[3] An additional 23 percent of newly diagnosed individuals received treatment that did not include medication. We study the effect of two policies designed to increase access to treatment: (1) improving insurance coverage of treatment and (2) increasing the supply of providers of

[1] https://www.hhs.gov/opioids/about-the-epidemic/index.html

[2] https://www.drugabuse.gov/publications/drugfacts/fentanyl

[3] As we describe below, there are three medications approved to treat OUD; our data primarily capture buprenorphine, by far the most common medication utilized.

medication-assisted treatment or MAT (specifically, prescribers of buprenorphine, the most commonly utilized medication).

To examine how insurance coverage affects treatment, we evaluate the effect of insurance parity laws, which require commercial plans to provide equal coverage for substance use treatment as for other medical conditions, on treatment utilization and outcomes. We use a difference-in-differences strategy that compares small group and large group enrollees before and after the Affordable Care Act extended parity requirements to small group plans effective 2014; parity was previously mandated for large group plans as of 2010 via the Mental Health Parity and Addiction Equity Act of 2008. We find that the extension of parity to small groups increased the utilization of residential treatment among small-group enrollees newly diagnosed with OUD, but *decreased* the utilization of MAT, resulting in no net change in the propensity to receive any treatment. We also find no statistically significant impacts on clinical outcomes or medical spending as a result of parity.

Given the decrease in MAT utilization as a result of parity, we next consider the potential impact of MAT supply-side policies that would increase the number of clinicians eligible to prescribe buprenorphine. Examples of such policies include the hub-and-spoke model in Vermont,[4] or lowering training requirements for buprenorphine prescribers.[5] For this analysis, we collected data via a Freedom of Information Act request on the number of providers in each U.S. county who have acquired the requisite credential to prescribe buprenorphine, and created a normalized measure of provider supply, *BP MD Share*, by dividing this number by the number of "frontline" physicians in a county.[6] We estimate models relating patients' treatment decisions to *BP MD Share* in the relevant county and year, controlling for patient and plan characteristics, county and county-year covariates, and state-by-year fixed effects.[7]

We find that increases in *BP MD Share* are associated with greater utilization of MAT

[4] As described in Brooklyn and Sigmon (2017), the hub-and-spoke model creates centers of addiction expertise ("hubs") to increase the willingness of "spokes" (primary care providers) to provide addiction care by offering support to these providers such as intake, induction, and care for patients who destabilize.

[5] In the final days of the Trump administration, the Department of Health and Human Services issued new addiction treatment guidelines exempting physicians with a narcotics prescribing license from mandatory training before prescribing buprenorphine. The guidelines were withdrawn in early 2021 by the leadership of the Department of Health and Human Services installed by President Biden; officials reportedly cited the need for additional study.

[6] As we discuss in the text, we define "frontline" physicians as primary care physicians and psychiatrists. For all but the final year of our study period, non-physicians were not eligible to prescribe these medications.

[7] As we explain below, the data are too thin to support county fixed effects, but we include as a control variable the initial BP MD Share for each county.

(with or without additional outpatient services) in the six months following diagnosis, lower utilization of medication-free outpatient treatment, and modest improvements in clinical outcomes. This analysis relies on the assumption that variation in *BP MD share* over time and across counties (controlling for the initial county *BP MD share*, as well as state-year fixed effects) is orthogonal to other determinants of patients' treatment decisions and outcomes. This assumption could be violated if, for example, counties with the largest increases in *BP MD Share* within a given state diagnose more patients with OUD, perhaps due to greater physician awareness and engagement. To assess the potential impact of omitted variables such as these, we confirm the results are robust to (1) excluding county-year covariates, which may be correlated with unobserved covariates; and (2) excluding patients who receive treatment on the same day of diagnosis, which (as we discuss below) may arise due to changes in physicians' diagnosing behavior (i.e., the "diagnosis margin.")

Supplementary analyses show the benefits of increasing *BP MD Share* are most pronounced when counties have below-median values of *BP MD Share*.[8] In these county-years, increases in *BP MD Share* are associated with greater utilization of MAT but not with reductions in other treatment modalities, driving an increase in the overall propensity to receive treatment and substantially larger clinical benefits than in the entire sample. In fact, the data suggest that increasing *BP MD Share* in counties at above-median levels is not associated with higher overall treatment rates nor with significant improvements in clinical outcomes, although rates of MAT do increase (at the expense of medication-free regimens).

While most prior studies utilize aggregate data including the Medicaid and uninsured population or focus specifically on the Medicaid population, there are advantages to studying the commercially insured population. First, patient churn in this population is considerably less, enabling the researcher to track outcomes over time, and to study patients conditional on prior health history (e.g., of substance use disorder). Focusing on the newly diagnosed enables us to compare individuals at similar stages of their disease across areas and over time, and isolates changes in the extensive treatment margin. Second, low-income, non-disabled adults were not generally covered by Medicaid until the Affordable Care Act expansions

[8]The national population-weighted median value of (*BP MD Share*) is 7.5 percent over the study period, 2009-2017. In these analyses, counties may shift from below to above median over time.

beginning in 2014, limiting the study period for the Medicaid population. Last, although survey data suggests OUD prevalence among commercially-insured adults is only one-third that among the uninsured and publicly insured (SAMHSA, 2017a), due to the sheer size of the commercially-insured population, the total numbers of commercially-insured and publicly insured adults suffering from OUD are similar. Hence, any effort to increase treatment rates will need to address the barriers across a range of populations.

Overall, our results suggest that increasing the generosity of commercial insurance coverage for OUD treatment did not increase the utilization of MAT, the clinical standard of care. Rather, we find that more generous coverage increases utilization of a higher-cost care alternative, residential care, whose effectiveness has not been established in the clinical literature. In contrast, we find suggestive evidence that utilization of MAT increases with availability of physicians eligible to prescribe buprenorphine, controlling for other observable and potentially unobservable factors (i.e., via state-year fixed effects). In areas with below-median access to buprenorphine prescribers, increases in buprenorphine prescribers lead to higher treatment rates and improved clinical outcomes. In areas with above-median access, we find patients substitute away from medication-free treatment and toward MAT, meaning that the extensive margin of receiving any treatment is not significantly affected. Additional research is needed to develop and assess robust ways to increase the share of patients who receive treatment for this deadly disorder.

The paper proceeds in five additional sections. Section 2 provides background on OUD, the medications used to treat it, and prior related literature. Section 3 describes our data sources and presents key descriptive findings. Section 4 outlines both empirical analyses, and Section 5 presents the main results, robustness checks, and extensions. Section 6 concludes.

2 Background

2.1 Prevalence and treatment of opioid use disorder

The most widely cited estimates of the prevalence of substance use disorder in the U.S. derive from the National Survey on Drug Use and Health (NSDUH), which conducts face-to-face

interviews with approximately 70,000 individuals each year. Using the NSDUH, the CDC estimated that 1.6 million people met the criteria for an opioid use disorder (OUD) in 2019. A larger population is estimated to have misused opioids (10.1 million) but did not meet the criteria for an OUD.[9]

OUD is treated by a diverse set of providers and therapies. A key distinction between treatment types is whether or not they include medication, often referred to as"medication-assisted treatment," or MAT. Two types of medications are currently approved for the long-term treatment of opioid dependence: opioid agonists and opioid antagonists. Opioid agonists are themselves opioids, but they activate opioid receptors for longer durations and at a lower intensity than analgesic opioids, and thus prevent withdrawal symptoms without producing the same euphoric effect. The most studied agonist is methadone, which was approved for the treatment of opioid dependence in 1972, and is taken orally once per day. Buprenorphine (also sold under brand names such as Suboxone and Zubsolv) was approved by the FDA for treatment of opioid addiction in 2002. Buprenorphine is a partial agonist, meaning that it has a ceiling effect, thus limiting its potential for abuse relative to methadone. In addition, it is commonly delivered in combination form with naloxone, which prevents the opioid from acting if injected, further decreasing its risk of abuse. While methadone can only be dispensed in federally licensed facilities, buprenorphine can be prescribed for take-home use by physicians who obtain a waiver from the Drug Enforcement Administration (DEA).[10] The second type of medication used to treat OUD are opioid antagonists, which block, rather than activate, opioid receptors so that patients who take antagonists and then use an opioid do not experience the opioid's effects. The only FDA-approved antagonist is naltrexone. The extended release version (a monthly injection with the brand name Vivitrol) was approved to treat OUD in 2010. Because it has no abuse potential, Vivitrol is often favored for use in criminal justice settings.

[9]The Diagnostic and Statistical Manual of Mental Disorders (DSM-5), defines a diagnosis of "substance use disorder" as "when recurrent use causes clinically and functionally significant impairment, such as health problems, disability, and failure to meet major responsibilities." Diagnostic criteria include evidence of impaired control, social impairment, risky use, and pharmacological criteria. (see Appendix A for further details) This definition is distinct from other commonly used terms such as "dependence" or "misuse." Misuse is defined as use in any way not directed by a doctor, including use without a prescription of one's own, and use in greater amounts, more often, or for a lengthier period of time than prescribed.

[10]Buprenorphine is available as a sublingual film or tablet (typically taken once or twice daily), and since early 2018, as a monthly arm patch.

Most medication-assisted therapy is known as "maintenance therapy," meaning that patients are expected to continue taking the medication for an extended period of time (possibly indefinitely).[11] In contrast, medication-free treatment generally begins with detoxification and is followed by abstinence-supporting care. This care can be delivered in an inpatient or residential setting, or in varying intensities on an outpatient basis.[12]

An interesting feature of substance abuse treatment is that a substantial amount of care is delivered by specialty providers, including dedicated substance abuse treatment facilities. These providers are generally licensed by states, which vary in their licensing requirements. However, in many states, it is not necessary to have a prescribing professional on staff to be a licensed treatment provider. In addition, many facilities also follow an abstinence model of treatment. During our study period, the share of substance abuse treatment facilities offering medication-assisted treatment increased from just 22% in 2009 to a (still low) 38% in 2017 (SAMSHA, 2019).

A significant body of clinical research supports medication-assisted treatment (MAT).[13] In clinical trials that compare patients receiving these medications with a control placebo group, those receiving MAT with agonists experienced significant reductions in other opioid use (as measured through hair or urine tests, or self-reports) and increased retention in treatment programs.[14] There are far fewer studies of extended-release naltrexone, but the literature thus far generally finds improved outcomes, albeit at lower rates than agonist therapy (Lee et al., 2018; Connery, 2015). On the other hand, there is relatively little evidence of the effectiveness of any treatment regimen that does not include medication.

Clinical studies do not speak directly to the effects of MAT outside of tightly controlled clinical trial settings. There are non-clinical, retrospective studies that use insurance claims

[11] Methadone and buprenorphine are also sometimes used for detoxification, meaning that patients are given methadone and buprenorphine to manage withdrawal symptoms in either an inpatient or outpatient setting and gradually tapered over the course of the detoxification period. (SAMHSA (2017b) estimates that this treatment accounts for less than 10% of admissions using medication).

[12] Outpatient care includes higher intensity "day treatment" (known as "partial hospitalization" if the program exceeds 20 hours of care per week or "intensive outpatient treatment" for programs of 9-20 hours per week)' as well as standard outpatient programs (<9 hours per week) (American Society of Addiction Medicine, 2018). Many treatment programs take a "step down" approach where higher intensity services are offered to patients with the most severe disorders, who may transition over time to less intense levels of care.

[13] See Mattick et al. (2009) and Mattick et al. (2014) for a review; we summarize the evidence further in Appendix B.

[14] In many trials, the control and treatment groups also received additional services such as psychotherapy, as is generally recommended, but studies comparing MAT with and without psychotherapy generally fail to find a statistically significant difference in outcomes (e.g. Sigmon et al., 2016).

data to compare patients receiving MAT to other patients; these have found reductions in spending and improvements in outcomes for patients receiving MAT, but they generally do not control for selection into treatment (e.g., Kessel et al., 2018; Larochelle et al., 2018; Wakeman et al., 2020)

2.2 Parity laws

In the private insurance market, so-called "parity laws" have expanded coverage for OUD treatment. Parity laws require private insurance plans to offer equivalently generous coverage (measured by cost sharing, day limits, etc.) for mental health and/or substance abuse services as they do for general medical and surgical services. The first federal parity statute was the Mental Health Parity Act of 1996 (MHPA), but it explicitly exempted substance use disorders. As a result, several states passed parity laws for substance use disorders prior to the second federal parity action, the Mental Health Parity and Addiction Equity Act (MHPAEA), which was passed in 2008 and required parity for substance use disorders effective 2010.[15] However, both MHPAEA and most (if not all) of the earlier state laws excluded individuals and small groups (i.e., groups with fewer than 50 members) (Buchmueller et al., 2007). The Affordable Care Act extended parity to small groups in 2014. Because our data begins in 2008, we study this last parity action, using large group enrollees as the control group for our difference-in-differences study.[16]

Evidence regarding the impact of parity laws on treatment utilization has been mixed (see Peterson and Busch, 2018, for a review). Prior studies generally make use of two different types of data sources: (1) claims data (similar to this paper), and (2) data from treatment facilities. Most studies that use claims data (including this study) find no impact of parity on the overall utilization rate of treatment, although they show that parity laws reduce patient cost-sharing and increase the use of out-of-network services (Busch et al., 2014; Ettner et al., 2016; McGinty et al., 2015). On the other hand, studies using facility-level data generally find that the volume of "treatment admissions" increased as a result of parity (e.g., Wen et al., 2013; Maclean et al., 2017). Because these studies use data on treatment admissions,

[15] To be more precise, MHPAEA required parity for policy years beginning after October 9, 2009, but private policy years are typically calendar years. (Source: CMS Fact Sheet: The Mental Health Parity and Addiction Equity Act)

[16] Parity was also extended to individual plans, but we do not consider these enrollees in our study given other large changes to the individual insurance market by the ACA.

however, the effects will combine increases in OUD prevalence, extensive margin increases in treatment, and intensive margin increases in treatment. These data are also unlikely to capture most buprenorphine treatment, which is generally prescribed in-office. Our analysis extends prior work on the impact of parity by using a more recent natural experiment, isolating its effects on MAT, and examining health outcomes.

2.3 Provider supply

Another potential barrier to treatment is the availability of providers. In the case of medication-assisted treatment, provider supply may be limited by the strict regulation of medications used to treat OUD. Methadone can only be dispensed at federally licensed Opioid Treatment Programs (OTPs, commonly known as methadone clinics). Buprenorphine can be prescribed for at-home use, but only by physicians who have obtained an "X" waiver.[17] Physicians obtain waivers by completing an eight-hour training course or through board certification in addiction medicine. In 2016, nurse practitioners and physician assistants became eligible for waivers with 24 hours of training.[18] See Appendix C for a broader discussion of regulation regarding controlled substances used to treat substance abuse disorders.

The top panel of Figure 1 shows trends in the supply of Opioid Treatment Programs and X waivers from 2004-2017. While the number of OTPs has been fairly stable over the past fifteen years (around 1,300 nationwide), there has been a steady increase in the number of waivered prescribers since the approval of buprenorphine, with a pronounced surge after 2016. The bottom panel graphs estimates of the number of patients using methadone, buprenorphine, and naltrexone, constructed from national, public data sources. It shows that the number of patients using buprenorphine for OUD has climbed in tandem with the increase in waivered providers; we estimate it exceeded 1.2 million unique users in 2016, with significantly fewer patients using methadone (around 320,000) and naltrexone (around 30,000).

There are relatively few studies of the effects of increasing provider supply on treatment utilization and outcomes. Swensen (2015) exploits county-level changes in substance abuse

[17] These waivers were created in the Drug Addiction Treatment Act of 2000. However, buprenporphine, the first drug to fall under the Act's requirements, was approved by the FDA for the treatment of opioid use disorder in 2002.

[18] Waivers are subject to legislated patient limits—originally 30 for all providers; now 100 for prescribers in the first year and 275 for those who apply after their first year for an increase.

facilities and finds a reduction in fatal overdose rates in counties with increases in treatment facilities. Our study is complementary: we use patient-level data, which enables us to explore the impact of interventions (both demand and supply-side) on specific treatment modalities and clinical outcomes, and allows for a richer set of controls. Another related study, Wen et al. (2018), shows an association between buprenorphine provider supply and buprenorphine prescribing in Medicaid at the state-level, but given the unit of observation cannot control for other policies that may vary at the state-year level. Our study includes state-year fixed effects to account for this variation.

3 Data

3.1 Private Insurance Claims Data

Our primary data are insurance claims from the Health Care Cost Institute (HCCI) dataset for calendar years 2008-2017. HCCI aggregates data from three large national insurers who jointly cover one-quarter of the non-elderly, commercially insured population and contains data on members from all fifty states and the District of Columbia. Relative to the national commercially insured population, HCCI is more concentrated in urban areas. Cooper et al. (2019) note that the HCCI data appears to be more geographically comprehensive than the MarketScan database, the other leading source for commercial claims data. We restrict our analysis sample to enrollees between the ages of 18 and 64 who receive medical, mental health, and prescription drug benefits from their primary insurer.[19] After applying this restriction, our baseline sample contains 12-15 million individuals per month, corresponding to about 15% of the commercially insured 18-64 population.

[19]Some large employers choose to "carve out" mental or pharmaceutical benefits to companies other than their insurance carrier, e.g. to a pharmaceutical benefits management company (PBM). In such cases, we lack comprehensive claims information.

3.1.1 Identifying patients with opioid use disorder (OUD)

We identify enrollees with OUD in two ways: (1) inclusion of an OUD diagnosis on any non-lab claim;[20] (2) receipt of buprenorphine formulations used for the treatment of OUD.[21] We add the second route because prescription drug claims lack diagnosis codes, so individuals who are treating their OUD solely with buprenorphine (or whose other treatment services are not included in insurance claims, e.g. Narcotics Anonymous meetings) may not have an OUD diagnosis in our data.[22] During the study period, we find OUD prevalence in our sample increased steadily from 1.7 to 3.9 per 1,000 enrollees. By comparison, data from the NSDUH (which relies on self-reports) shows similar prevalence among the privately-insured for 2017, but a smaller increase since 2008—from 4.2 to 4.3 per 1,000 enrollees.

3.1.2 Defining a "new diagnosis" analysis sample

We restrict our analysis sample to patients with a "new" diagnosis of OUD, defined as patients whose first OUD-related claim in our data appears after a period of at least 12 months with no OUD-related claims. We further require that these patients be observed for an additional six months after diagnosis, so that we can explore the care they receive and a range of outcomes observable through claims data.[23] Limiting the sample to new diagnoses enables us to study clinical outcomes and spending for a sample of individuals with the same disease state, assuming no variation in physicians' diagnosing behavior,[24] and yields an analysis sample of approximately 9,000 patients per year.

We describe the composition of this sample in Figure 2. The figure confirms some of the demographic characteristics of the opioid crisis identified in prior literature: a disproportionate share of the sample is male (57%) and young (43% aged 18-34, as compared to 14% of all HCCI enrollment ages 18-64). Given the incidence in the young population, it

[20] We exclude lab claims because diagnoses on lab claims are sometimes listed when testing for the presence of a condition, even if the test was not positive.

[21] As described in Appendix A, some formulations of buprenorphine are primarily used for treatment of pain while others are used for treatment of OUD; these can be identified by the specific "NDC codes" included in claims.

[22] 44% of people receiving buprenorphine in a given year do not have an associated OUD diagnosis.

[23] Note that patients need not have claims during the followup period; however, they must continue to have insurance coverage through one of the carriers in HCCI in order to be included in the analysis sample. 1.5% of those included in the new diagnosis sample have no claims during the 6-month period post-diagnosis.

[24] The inclusion of state-year fixed effects in all models should absorb much of this variation, which is also unlikely to be correlated with small versus large-group treatment decisions.

is unsurprising that a sizeable share of the new diagnosis sample (23%) receives coverage through the policy of a parent or guardian. Figure 2 also provides the distribution of the sample by the year and setting of the patient's initial OUD diagnosis.[25] Nearly half the sample is diagnosed in a detox or treatment setting, and 14% are diagnosed in the ER. The remainder are primarily diagnosed during a non-treatment office visit, such as a physical, psychiatric evaluation, or visit for a different medical complaint.

3.1.3 Treatment, spending, and clinical outcomes of patients with new OUD diagnoses

For each newly diagnosed patient, we construct indicator variables for receiving different types of treatment in the six months post-diagnosis, indicator variables for experiencing specific adverse events in the six-months post-diagnosis, and also measure total medical spending in the pre-diagnosis and post-diagnosis periods.

We define three mutually exclusive treatment categories: MAT, Medication-free Residential, and Medication-free Outpatient. Mutually exclusive categories aid us in analyzing substitution across modalities. "MAT" includes patients receiving medication at any point in the 6-month post-diagnosis period. 93% of the MAT sample received buprenorphine.[26] The MAT sample includes patients who received medication as their only source of treatment in our data (67%), as well as patients who receive other treatment services in addition to medication (33%).[27] Defined this way, nearly 30% of newly diagnosed OUD patients received MAT in the six months following their diagnosis. Another 23% obtain medication-free

[25] The sample is roughly halved in size for 2017, as our claims data end in 2017 so we only have a 6-month followup period for patients diagnosed during the first half of the year. Setting aside 2017, the number of patients in the analysis sample does not increase over time, notwithstanding the previously documented increase in OUD prevalence among HCCI enrollees, because the share of HCCI enrollees receiving both mental health and prescription drug benefits through their primary insurer—a requirement for inclusion in our sample—is decreasing over time.

[26] We classify patients as receiving buprenorphine if they have at least one buprenorphine prescription drug claim in the six months following their diagnosis. Results are similar if we limit to prescriptions of at least 30 days' supply. Methadone and naltrexone are identified using procedure codes. Our data include relatively few methadone claims, and it is possible that some patients are paying for it out-of-pocket or receiving it free of charge. However, data from the National Survey of Substance Abuse Treatment Services suggest that only 10% of the 300,000 methadone patients per year in the US have private health insurance. IMS counts of buprenorphine suggests that about 57% of the 1.2 million buprenorphine patients in 2016 paid for their prescription using private insurance, leading to a buprenorphine utilization rate among privately insured patients that is about 20 times the utilization rate of methadone.

[27] MAT includes all individuals receiving medication, including the small share who receive both residential treatment and medication. Results from categorizations that are not mutually exclusive are very similar and available upon request.

services, which we subdivide into those receiving residential treatment (4%) and those receiving outpatient services only (19%). Table 1 summarizes our clinical and spending outcome measures for the full sample (column 1), and by treatment type (columns 2-5).

The first few rows report the incidence of three clinical outcome measures: overdoses, drug-related ER visits, and non-drug-related ER visits, all measured over the 6 months following a new diagnosis. We find that only 4.5% of our sample has an overdose claim during the post-diagnosis period; this rate likely understates the volume of overdoses because some overdoses may not result in any insurance claims (e.g., overdoses handled in the field by first responders). On the other hand, 26% of all newly-diagnosed OUD patients experiences one or more drug-related ER visits, which we define as any ER visits that include an overdose, drug dependence, poisoning, or withdrawal diagnosis code (again, excluding lab claims).[28] Finally, 23% of the sample visits the ER for non-drug-related reasons. Overall, the rate of adverse clinical outcomes post-diagnosis appears to be lowest among those receiving medication-assisted treatment (column 2), and highest among people receiving medication-free residential treatment (column 3). However, these patterns may reflect both selection into treatment as well as the causal effects of treatment.

The bottom rows of Table 1 summarizes average spending for each group in the six months before and after a new OUD diagnosis.[29] Average spending in the six months prior to diagnosis is high—nearly $12,000 (in CPI-adjusted 2017 dollars)—and it increases to more than $17,000 in the six months following diagnosis. Post-diagnosis spending for patients receiving medication-free treatment (columns 3 and 4) is significantly higher than post-diagnosis treatment spending for patients receiving MAT (column 2), reflecting both higher treatment spending and higher non-treatment spending for patients receiving medication-free treatment. However, patients receiving MAT also have lower pre-treatment spending, suggesting these raw comparisons are likely to suffer from selection bias. Notably, non-

[28] We summarize the most frequent primary diagnoses for these visits in Table A3.

[29] We assign claims to spending categories using a priority order system detailed in the Appendix that generally allocates spending to the "highest intensity" service provided on a given day. Allocating spending by day rather than by service allows us to capture treatment-related spending that is not billed as a "treatment service," such as physician billing for evaluation and management or lab services in a treatment program. However, it may also result in overcounting if patients receive non-treatment related services on the same day as a treatment service. We do not count detox as a treatment service.

treatment spending increases post-diagnosis for all patients except those receiving MAT.[30]

3.2 Prescriber Data

We use the individual's zip code and diagnosis year in the claims data to merge in county-year data on several variables, including our measure of access to buprenorphine, *BP MD Share*. This measure is constructed by taking the number of providers with waivers to prescribe buprenorphine and dividing by the number of primary care physicians and psychiatrists ("frontline providers") in the county-year. The numerator is constructed from data on the practice zipcode (at the time the waiver was granted) and waiver date of every provider granted a waiver to prescribe buprenorphine, which we obtained through a FOIA request to SAMHSA.[31] We use this source to estimate the number of waivered providers in every county and year.[32] The denominator is constructed from the Area Health Resource Files.[33] Normalizing the number of providers with waivers in this way serves two purposes. First, it addresses the fact that some counties have relatively low or high availability of medical professionals. A central county may provide care for residents of outlying counties, and failing to normalize for the density of medical professionals could yield misleading estimates of access. Second, this normalization is appropriate in light of potential policies to address access, e.g., easing the restrictions for prescribing buprenorphine or abbreviating training. PCPs and psychiatrists are among the likeliest targets of such interventions, as they are the primary frontline physicians encountering patients with OUD.[34]

Nationally, *BP MD Share* increased from 6.2% at the end of 2008 to 18.1% at the end of 2017. There is substantial variation in *BP MD Share* across locations and over time.

[30] Note that by construction, all pre-diagnosis spending is non-treatment spending.

[31] At present, only limited historical data is publicly available, specifically state-level counts of waivers.

[32] Unfortunately, although the data records provider moves, it does not record the date on which a move occurs. We use the first recorded location to construct BP MD share. In unreported results, we confirm that using the last reported location does not alter the results. Approximately 5% of providers experience at least one move in our data. We also do not observe if or when providers stop practicing or prescribing buprenorphine.

[33] The AHRF obtains these measures from the American Medical Association's *Masterfile* and defines primary care physicians as MDs and DOs who provide direct patient care and practice principally in one of the four primary care specialties: general or family practice, general internal medicine, pediatrics, and obstetrics and gynecology.

[34] Addiction medicine specialists are often psychiatrists, therefore many of these specialists are included in the denominator. One exception to the waiver process is that patients can also be dispensed buprenorphine at OTPs (although they cannot receive a prescription for take-home use unless issued by a waivered provider). However, survey data of these facilities suggest that the number of patients receiving buprenorphine at an OTP is relatively small (about 50,000 in 2015, less than 5% of the total estimated number of patients receiving buprenorphine) (Alderks, 2016) and it is likely that these OTPs may employ waivered providers. Thus, we do not make adjustments for OTP locations in our analysis.

Figure 3 graphs the growth in state-level *BP MD Share* between 2008 and 2017 against the initial state-level *BP MD Share* in 2008. The figure identifies some early adopters (e.g., Vermont, Maine, New Mexico, Rhode Island and Utah) as well as late adopters (e.g., New Hampshire, Idaho, Kentucky, Washington). It also shows that state-level *BP MD Share* does not converge over time: instead, there is a clear positive relationship between growth before and after 2008. This pattern implies attempts to instrument for access to buprenorphine using state-time variation (e.g., state-specific post-ACA Medicaid expansions) are unlikely to be orthogonal to other factors potentially affecting treatment utilization.[35] Thus, our analysis exploits cross-county variation in *BP MD Share*, and controls for state-year effects.

4 Empirical Strategy

We pursue two separate analyses of potential barriers to treatment. The first analysis exploits the extension in parity to small groups by the Affordable Care Act in 2014; as noted earlier, the MHPAEA had previously required parity for large groups in 2010. These results reveal the impact of increasing the generosity of insurance coverage (a demand-side intervention) on different types of OUD treatment. The second analysis explores the relationship between access to buprenorphine providers and patient outcomes. This analysis speaks to the impact of a more targeted, supply-side policy intervention.

4.1 Effects of Insurance Parity on OUD Treatment and Outcomes

To study the effect of insurance parity, we use a difference-in-differences specification that compares small group to large group enrollees before and after parity was extended to small groups in 2014. For this analysis, we apply three additional restrictions to our analysis sample of newly diagnosed OUD patients. First, we limit the estimation sample to fully-insured enrollees, so as to maximize the comparability of the treatment (small group) and control (large group) samples. Small group enrollees are nearly always enrolled in fully-insured plans, whereas the majority of large group enrollees are in self-insured plans. Sponsors of

[35] Indeed, such an attempt on our part showed evidence of "pre trends," as expansion states were generally increasing access to buprenorphine both before and after the Medicaid expansion took place.

self-insured plans often influence the type and degree of utilization review, whereas insurers typically set these terms for fully-insured enrollees. Second, we exclude the first year of data (2009) as parity was not required uniformly of all large group plans until 2010. Finally, we also drop patients newly diagnosed during the second half of 2013 in the event their spending (partly in 2014) reflects the policy change. Summary statistics (Appendix Table D1) show that patient characteristics in this smaller sample (which still contains over 28,000 observations) are very similar to those of the full sample. Using this sample, we estimate the following specification:

$$Y_{ist} = \alpha + \beta X_i + \kappa \text{SmallGroup}_i \times \text{Post}_{it} + \omega \text{SmallGroup}_i + \gamma_{st} + \epsilon_{ist} \quad (1)$$

for each newly-diagnosed individual i living in state s and diagnosed in year t. The dependent variables Y_{ist} are indicator variables for different treatment modalities, spending measures, and clinical outcome measures.

The coefficient of interest is κ, which captures the differential effect of being enrolled in a small group plan after parity was extended to small groups in 2014. We control for patient and insurance characteristics X_i (sex, age band, plan type, indicator for a high-deductible healthplan), as well as state-year fixed effects γ_{st}. For dependent variables Y_{ist}, we use binary measures reflecting treatment utilization, binary measures of clinical outcomes, and continuous measures of spending. We transform spending measures using $log(x + 1)$.

To explore pre-trends, we also plot coefficients κ_t from the expanded specification below:

$$Y_{ist} = \alpha + \beta X_i + \kappa_t \text{SmallGroup}_i \times \text{I(Year = t)} + \gamma_{st} + \epsilon_{ist} \quad (2)$$

One threat to a causal interpretation of the results is the possibility of changes in the composition of small and large group members which are also correlated with changes in utilization. For example, in other work, we report that older patients became less likely to utilize buprenorphine over this period (Shen et al., 2020). If small group enrollees are skewing younger or older over time, such a trend could bias the results. Thus, in the Appendix, we also provide estimates of models where we interact each of our controls X_i with the *Post* indicator.

4.2 Effects of Access to Buprenorphine Prescribers on Treatment and Outcomes

Our second analysis estimates the relationship between changes in the local availability of buprenorphine providers and the propensity of newly-diagnosed OUD patients to receive treatment (with or without buprenorphine), as well as clinical and spending outcomes.

For each patient i living in county c and diagnosed in year t, we regress treatment utilization, clinical, and spending outcome measures Y_{ict} on our measure of buprenorphine access using the following specification:

$$Y_{ict} = \alpha + \beta X_i + \delta \text{BP MD Share}_{ct} + \mu \text{BP MD Share}_{c,2008} + \lambda Z_{ct} + \gamma_{st} + \epsilon_{ict}. \quad (3)$$

Our main coefficient of interest is δ, which captures the relationship between the dependent variable (e.g., an indicator for receiving MAT) and *BP MD Share*$_{ct}$. In addition to the same patient-level controls X_i previously described, we also include county-year covariates Z_{ct} that may impact our outcome measures (average health care spending for commercially-insured adults, to capture variation in local price levels and healthcare utilization, and the unemployment rate, to capture economic conditions which may independently affect health and health-related spending).[36] The unemployment rate has specifically been found to be positively related to adverse opioid-related events (Hollingsworth, Ruhm, and Simon, 2017).

We again include state-year fixed effects (γ_{st}) to help control for fixed and time-varying factors at the state level that may affect both *BP MD Share* and the various outcomes of interest. For example, increases in *BP MD Share* may coincide with increases in state funding for substance abuse treatment or other state initiatives that affect MAT (e.g., the state-level Medicaid expansions occurring in 2014+), which could independently affect the propensity to initiate MAT. Finally, to control for county-level unobservables that might bias the coefficient of interest, we include the "initial" county-level *BP MD Share* (measured in 2008, the year prior to the start of the study period). We include this lagged measure in lieu of county fixed effects because the median county in our sample contains only six patients

[36] Average county-year spending is calculated using HCCI claims for all non-elderly enrollees with both medical and prescription claims data; the county-year unemployment rate is from the BLS Local Area Unemployment Statistics.

across all years. Initial *BP MD Share* will capture relevant county-specific, time-invariant characteristics that may affect both *BP MD Share* and our outcomes of interest, such as pre-existing substance abuse treatment infrastructure. Because our variable of interest (*BP MD Share*) varies at the county-year level, we report standard errors clustered by county-year.

One concern with this empirical strategy is that our sample might be endogenously selected as a response to the variable of interest. For example, if treatment capacity directly influences the diagnosis margin, the population diagnosed with OUD might be systematically different in counties experiencing greater increases in *BP MD Share*. Finkelstein et al. (2017) finds that regional variation in "diagnostic intensity" amplifies regional differences in estimated health. Although state-level variation (and changes) in diagnostic intensity in our setting are absorbed through fixed effects, county-level changes in diagnosis margins could pose a problem for identification. We attempt to address this concern in Section 5 by further restricting the sample to exclude individuals who receive treatment on the same day they are diagnosed. Around 29% of our sample is diagnosed (per the claims data) on the first day of treatment. If more providers are trained to dispense buprenorphine, they may diagnose more marginal cases of it because they have tools to help treat it; such cases are likelier to result in same-day treatment. As implied by Figure 2, the sample excluding these patients will primarily consist of patients diagnosed in ER or non-treatment office-based settings, including psychiatric visits. Summary statistics for this sample, in which treatment rates are quite a bit lower, as expected, are in Appendix Table D1.

A second concern is that omitted variables may bias the coefficient of interest. For example, unobserved economic conditions may both increase the prevalence of OUD and drive physicians to seek waivers, but these conditions might also reduce the likelihood that patients choose to receive treatment for their disease (perhaps due to a heightened need to work, or concerns about cost-sharing for treatment). Alternatively, increases in *BP MD Share* may coincide with other county-specific policy changes or investments in treatment accessibility or capacity, in which case any changes in outcomes would also reflect these unobserved reforms. Although we cannot fully address the concerns associated with omitted variables, we present estimates of our baseline specification that exclude county-year covariates to assess whether the results are sensitive to omitting these controls.

5 Results

5.1 Effects of Post-ACA Parity for Small Groups on OUD Treatment and Outcomes

In this section, we present results obtained by comparing the post-diagnosis treatment decisions and clinical and spending outcomes of patients with small group coverage relative to patients with large group coverage, before and after the extension of parity requirements to small groups.

Table 2 shows the impact of parity on the propensity for patients to receive treatment of any kind as well as specific types of treatment within six months of diagnosis using equation (1). While parity may have impacted all types of treatment, our prior is that the effect will be most pronounced for residential treatment, which is particularly expensive and hence likely to be subject to the most restrictive prior authorization or utilization limits before parity was mandated.[37] Column (1) shows that extending parity to small groups did not increase the probability that a newly diagnosed small-group enrollee received any treatment. Columns (2)-(4) show that in fact, parity reduced the likelihood that patients received MAT, while increasing the likelihood that patients received medication-free treatment, in particular medication-free residential treatment. The coefficient estimates on *Small Group* $\times$ *Post*, which captures the average effect of parity on small versus large-group employees, are statistically significant at α=0.01 for residential treatment and α= 0.05 for MAT. The magnitude of the residential effect is quite large: the point estimate implies parity increases utilization of residential care by 0.014 relative to a pre-period small group mean of 0.033, or 48 percent.[38] Proportionally, the impact on medication-assisted treatment (8.7 percent of baseline) is smaller, but MAT has a much higher baseline utilization level, at 0.38 for small-group sample members during the pre-period. The net effect is that parity does not increase the

[37] As previously noted, the specific treatment types are defined to be mutually exclusive. Patients with medication claims at any point during the 6-month post-diagnosis period are classified under"MAT." Of the 1,368 newly diagnosed patients who received residential treatment in the sample used for the parity analysis, 285 are classified in the MAT category. Results are insensitive to adding them to the residential category.

[38] The point estimate (standard error) obtained when defining "residential" to include patients who receive medication as well as residential care is 0.015, which corresponds to an increase of 43 percent relative to the pre-period small group mean of .035 using this definition for residential care.

odds of receiving any treatment; rather it appears to lead to substitution away from MAT and toward residential care which rarely includes it.[39]

Many of the included controls are statistically significant and of independent interest, albeit not the focus of this study. Treatment probabilities are generally decreasing with age and are lower for females. We also find that employees are more likely to receive MAT, while dependents are more likely to receive medication-free care (both residential and outpatient), even after controlling for age and gender.

To check the parallel trends assumption, we also estimated models interacting the small group indicator with individual year dummies (as represented in equation 2 above). Figure 4 plots the coefficient estimates on these interaction terms, where the omitted year is 2010. There is no evidence of a pre-ACA difference in utilization trends for small versus large-group enrollees. The decline in the use of MAT relative to large groups is pronounced between 2014 and 2016, and lessens in 2017, a year during which *BP MD Share* also surges.

We next examine how clinical outcomes evolved post-parity for newly diagnosed OUD patients in small-group plans relative to large-group plans. Table 3 presents the same difference-in-differences specification as in Table 2, but substituting the indicators for treatment with indicators for specific adverse clinical events during each patient's six-month post-diagnosis period. We do not find any significant effects of small-group parity on the probability of these events, and all of the coefficient estimates are positive, suggesting that the substitution of medication-free care for MAT as a result of parity may have been harmful. Plots of yearly interactions with the small group indicator also show no evidence of pre-trends (see Appendix Figure D1).

Table 4 contains the results for spending outcomes: treatment spending, non-treatment spending, and total spending. We find parity did not result in higher treatment spending among patients newly diagnosed with OUD, a result that may appear surprising in light of the high average costs of residential care. However, residential treatment is fairly rare, and the increase in spending on this category is more than offset by the reduction in MAT. We also do not find statistically significant changes in non-treatment or total spending (treatment

[39] Given the small sample for residential treatment, we also estimated models using indicators for any residential treatment (i.e., with or without medication), which occurs for 4.8% of the sample. The results are qualitatively similar and available upon request.

and non-treatment combined) as a result of parity. Overall, the estimates are imprecise, however, so it is not possible to rule out sizeable changes in spending.

As discussed above, the estimates of the impact of parity may be biased if small group patients differ from large group patients in ways that are correlated with their insurance coverage, have differential trends in outcomes, and for which we do not control in the main specification. For example, if our sample of small group enrollees skews younger over time, and younger enrollees experienced different trends in utilization and outcomes in the post-parity years of our sample for reasons unrelated to parity, the coefficient estimates may be biased. As a robustness check, we supplement the specifications in Tables 2-4 with interactions between each patient-level observable and a post-parity indicator (Appendix Tables D2-D4). Including these controls does not change our finding of significant substitution of treatments as a result of parity, and it has relatively limited impact on any of the coefficient estimates capturing the impact of parity on clinical or spending outcomes, suggesting that such factors are unlikely to be a significant source of bias.

Collectively, these results suggest that coverage limitations present in small group policies pre-ACA constrained patients' ability to access residential care, but not MAT, and that extending parity likely decreased the use of MAT due to substitution of other treatment modalities.

5.2 Effects of Access to Buprenorphine Prescribers on Treatment and Outcomes

In this section, we examine the relationship between increases in *BP MD Share* in a patient's county and the probability that a patient receives medication-assisted or medication-free treatment. We also explore the implications for treatment and non-treatment spending, as well as adverse health events.

5.2.1 Baseline specification

In Table 5, we report estimates of equation (3) using indicators for receiving different types of treatment in the post-period (i.e., the six months following a new diagnosis) as dependent variables. Again, we do not find that this policy lever is associated with a significant change

in the probability that a newly diagnosed OUD patient receives any treatment (column 1). We again see evidence of substitution of treatments, but in the opposite direction of that observed in the parity analysis: patients are significantly likelier to receive MAT if their local access to it (as measured by *BP MD Share*) increases (column 2), and less likely to receive medication-free outpatient treatment (column 4).

We can interpret the magnitudes of the coefficient estimates by considering the effect of the median county increase *BP MD Share* between 2008-2017, 8.8 percentage points. An increase of this size is associated with an estimated increase of 1.5 percentage points (+/- 0.4 percentage points using the 95% confidence interval) in the probability that a newly diagnosed patient with OUD receives MAT. This increase is small, albeit not trivial, as compared to the overall sample mean of 30 percent. However, it is largely offset by a statistically significant decrease in medication-free outpatient therapy. Thus, while patients are significantly more likely to receive MAT when more providers can prescribe it, they are not, on average, significantly more likely to receive any treatment.

Next, we consider the relationship between an increase in *BP MD Share* and indicators for post-diagnosis clinical outcomes. We find increases in *BP MD Share* correspond to statistically-significant reductions in the share of patients with drug-related ER visits (column 2). The estimates imply a county with the median increase in *BP MD Share* experiences a reduction in drug-related ER visits of one percentage point, relative to a sample mean of 26 percentage points. We find no statistically significant relationships with the other clinical outcomes (overdose and "other" ER visits).

Table 7 considers the association between changes in buprenorphine provider supply and health care spending for OUD patients. The coefficient estimates are noisy and none are statistically significant at conventional levels. The point estimates suggest any modest increase in treatment spending is more than offset by reductions in non-treatment spending, yielding a net negative, but statistically insignificant, coefficient estimate for total spending. However, it is possible to rule out a total spending increase of more than 0.8% associated with the median county increase in *BP MD Share* from 2008-2017.[40] The coefficients on the

[40]This upper bound is obtained by adding 1.96 standard deviations to the mean estimate (.005), multiplied by the median county increase, 0.088.

control variables reveal that non-treatment spending and overall spending for newly diagnosed OUD patients are positively correlated with average healthcare spending for the entire commercially insured population in a county-year and that all three measures of healthcare spending are negatively correlated with the unemployment rate in the county. Treatment spending decreases with age, but overall spending increases. In addition, treatment spending is higher for males, but overall spending is lower.

In order to allay concerns that the diagnosis margin may be endogenous to local *BP MD Share*, we re-estimate all specifications after excluding patients who receive treatment on the same day of diagnosis (see Tables D5-D7 of the Appendix). Treatment utilization rates are lower for this group by construction, but we continue to find that county-level *BP MD Share* is positively associated with MAT use and negatively associated with residential and outpatient treatment use (Table D5), although the effect sizes are smaller and less precisely estimated. We also continue to find evidence of a reduction in drug-related ER visits (Table D6), suggesting that the clinical improvements are not driven by MAT treatment providers diagnosing less severe patients. Finally, we also find slightly stronger suggestive evidence ($p<.10$) of decreased post-diagnosis total spending as a result of increased *BP MD Share* in this sample, driven by decreases in both treatment-related and non-treatment-related spending (Table D7) .

As a second check on the robustness of these results, we re-estimate these models after dropping the county-year control variables. To the extent that these measures are correlated with unobserved county-year factors that may also be correlated with *BP MD Share*, this exercise provides some suggestive evidence that omitted county-year factors are not driving the results. The coefficient estimates of interest for all dependent variables, presented in Appendix Tables D8-D10 are very similar.

5.2.2 Nonlinear effect of BP MD Share

We hypothesize that the relationship between access to treatment and the share of providers who are waivered to prescribe buprenorphine may diminish at higher levels of *BP MD Share*. We test this hypothesis by interacting our main independent variable, *BP MD Share*, with an indicator that takes a value of 1 if a county's *BP MD Share* has surpassed the national

(population-weighted) median for a county during our sample years, 7.5 percent. This effectively allows for two different slopes (one below the median and one above the median) for the relationship between the outcome variables and *BP MD Share*.

Table 8 displays the results of this specification for OUD treatment. Column (2) confirms our hypothesis, showing that the relationship between the probability that a newly diagnosed patient receives MAT and *BP MD Share* is three times as large when *BP MD Share* is below rather than above the median. In addition, while there is almost complete substitution toward MAT and away from other treatment regimens at above-median values of *BP MD Share*, increases in MAT in below-median counties appear to translate one-for-one into higher treatment rates (i.e., there is no crowdout of other treatment modalities). Overall, we estimate that below the national median of 7.5 percent, each increase of 1 percentage point in county *BP MD Share* is associated with a 0.4 percentage point change in the probability a an individual diagnosed with OUD receives MAT, and a similar increase in the probability they receive any treatment at all.

Tables 9 and 10 presents the same specification estimated using clinical and spending outcomes as dependent variables. In Table 9, column (2) shows that the negative effect on drug-related ER visits is only statistically significant below the median BP MD Share, and column (3) shows that in this region of *BP MD Share*, other ER visits decline as well. In Table 10, we find that treatment spending increases with *BP MD Share* when it is below the median level (column 1), which is unsurprising given the lack of treatment substitution. Nevertheless, we do not find a significant increase in total spending even in this region of values (column 3), presumably due to the noisy estimated reductions in non-treatment spending. These results suggest that for places with below-median shares of waivered providers, increasing this share has the potential to significantly increase MAT utilization and to improve clinical outcomes for patients with OUD, without necessarily leading to increases in total spending.

6 Conclusion

As the U.S. opioid crisis continues, policymakers are exploring ways to expand access to treatment. Unfortunately, there is a lack of empirical evidence to guide funding and planning. This study attempts to fill some of the gap by exploring treatment among a large sample of commercially-insured patients newly-diagnosed with OUD during the period 2009-2017.

We focus on two potential barriers to treatment: (1) insurance coverage of substance use treatment, and (2) the availability of local physicians able to prescribe buprenorphine, the OUD treatment with the most robust clinical support. Using a difference-in-differences specification exploiting the extension of insurance parity to small groups beginning in 2014, and assuming treatment utilization for newly diagnosed small and large group enrollees would otherwise have similar trends (controlling for a range of patient and plan observables), we find that parity generated significant increases in residential treatment, and a decline in medication-assisted treatment. We find no net change in the propensity for newly diagnosed patients to receive any form of treatment, nor do we find statistically significant effects on clinical or spending outcomes, although the point estimates are noisy.

To examine the impact of expanding provider supply, we consider the relationship between treatment patterns and local access to providers with waivers to prescribe buprenorphine. We find that increases in *BP MD Share* are associated with greater utilization of MAT, and in counties at below-median levels of *BP MD Share*, this increase is not offset by substitution away from other treatment modalities. In these below-median counties, we also observe clear improvements in clinical outcomes, as measured by drug-related ER visits and other ER visits, when *BP MD Share* increases. Effects on spending in these counties are unclear: treatment spending rises, but appears at least partially offset by reductions in non-medical spending, yielding noisy estimates of the impact on total spending. Overall, these findings suggest that expanding access to prescribers is likely to increase uptake of MAT, but in areas where access is already relatively high, this increase is likely to come at the expense of other treatment modalities.

Together, our findings suggest that policy interventions aimed at expanding access to treatment have impacts on the treatment modality selected, but in many settings there is

no net affect on the propensity to receive any treatment. The clinical standard of care, medication-assisted treatment, appears to be more limited by provider access than by insurance coverage, while the most expensive type of care, residential care, appears to be limited by coverage restrictions. These findings likely reflect the segmented nature of substance abuse treatment, particularly with regard to medication. A significant amount of care is provided in specialty facilities, which typically lack waivered providers.[41] Going forward, future research on the determinants of the decision to seek care, and on the effectiveness of a more integrated care system for patients with OUD, would be extremely helpful in developing policy solutions.

[41] In our sample, 31% of people who received any treatment received treatment from a specialty facility. MAT rates were 26% for those who received some treatment from a specialty facility, and 71% for those who did not receive treatment from a specialty facility.

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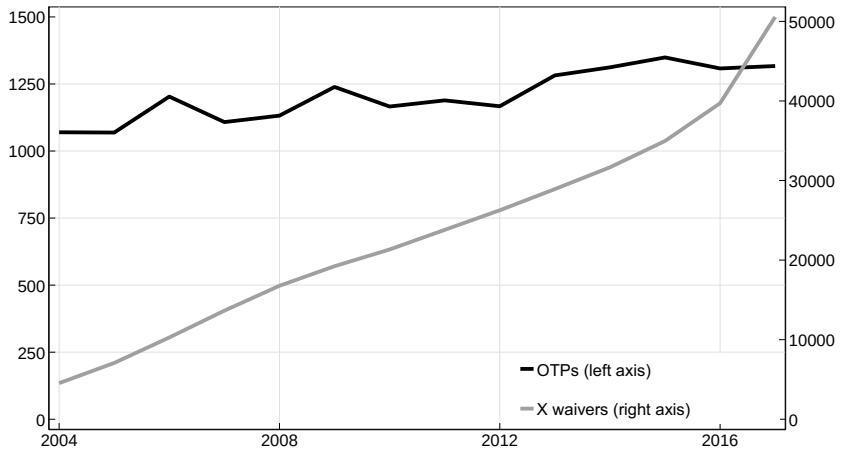
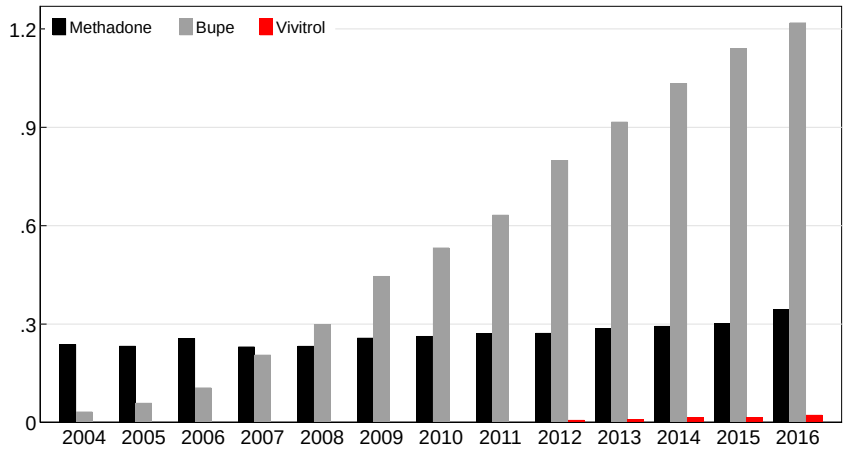
Figure 1: **Trends in supply and use of medication-assisted treatment**

(a) **Number of Opioid Treatment Programs and Waivered Prescribers, 2004-2017**

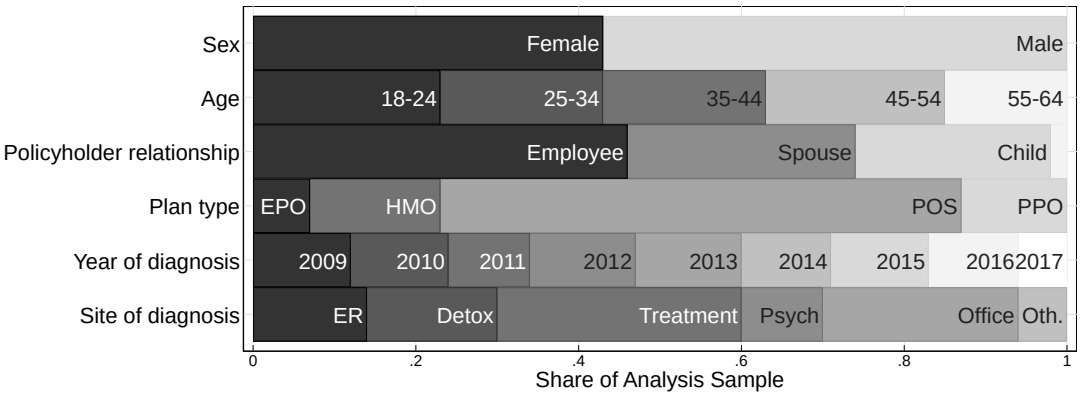


(b) **Number of patients using MAT, by drug , 2004-2016, in millions**



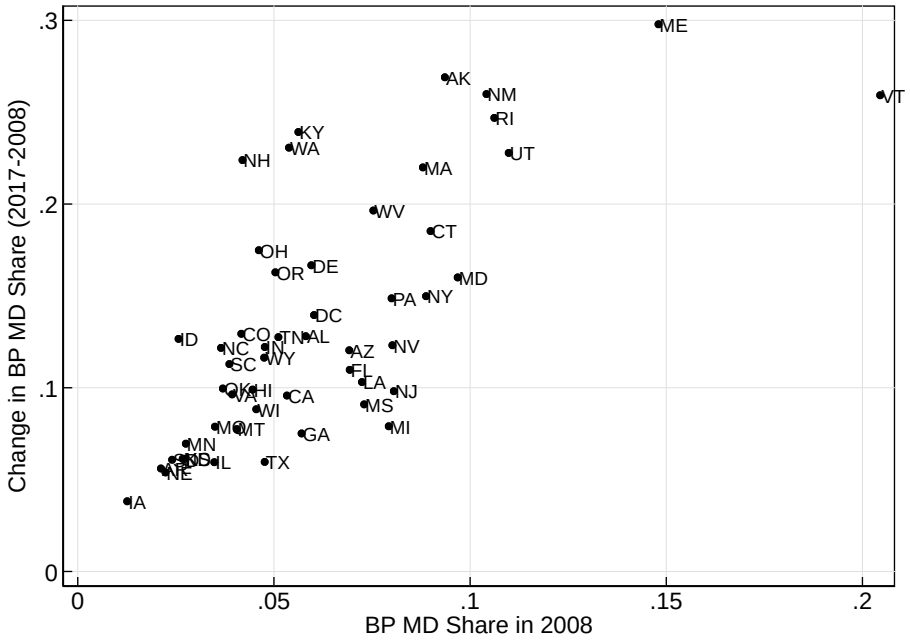
Notes: The top panel plots counts of OTPs from the National Survey of Substance Abuse Treatment Services (black) and counts of X waivers (grey) from SAMHSA public data. The bottom panel shows the annual number of patients using methadone (black), buprenorphine (grey), and Vivitrol (ER naltrexone; red) by year for the years 2004 through 2016, in millions. Methadone estimates are from the National Survey of Substance Abuse Treatment Services; buprenorphine estimates are from the IMS Total Patient Tracker assuming an average of 8 prescriptions per patient per year; Vivitrol estimates are from Alkermes 10K filings assuming a 50% Medicaid market share and prices of $500 per Medicaid and $1000 per private insurance dose.

Figure 2: **Summary statistics for new diagnosis sample**



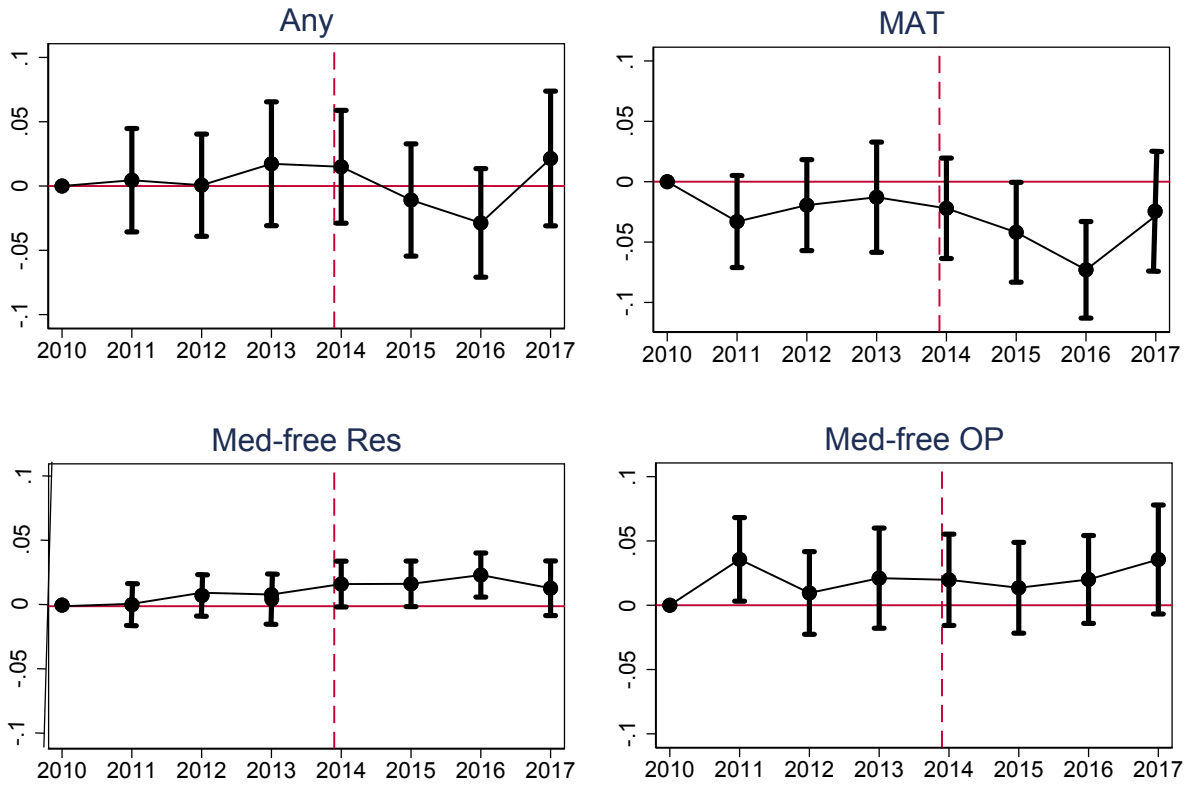
Notes: This figure summarizes key individual-level variables for the new diagnosis sample, as defined in the text. The policyholder relationship variable is missing for 2% of the sample and thus does not sum to 1. N=78,222.

Figure 3: **Relationship between change in state *BP MD Share* (2017-2008) and initial level in 2008**



Notes: This figure plots initial (2008) *BP MD Share* against the change in *BP MD Share* between 2008 and 2017. State-level estimates are obtained by cumulating SAMHSA's reports of new waivers by state and year and thus are subject to some error due to providers becoming inactive or moving states.

Figure 4: **Effect of small-group parity on treatment utilization**



Notes: This figure shows estimated coefficients and 95 percent confidence intervals on Small Group × year indicator variables in the sample of newly diagnosed OUD patients who were not diagnosed in the last six months of 2013. Dashed vertical lines indicate the post-period begins in 2014.

Table 1: **Mean clinical and spending outcomes by type of treatment received**

	(1) All	(2) MAT	(3) Med-free Res	(4) Med-free OP	(5) No TX
% of Sample	100.0	30.0	3.7	18.7	37.5
Clinical outcomes (%)					
Any OD	4.5	3.0	7.0	5.0	5.2
Drug-related ER	25.8	16.7	37.7	26.4	30.5
Other ER	22.8	18.0	24.1	19.1	27.0
6m Spending ($)					
Before Diagnosis	11,934	7,695	11,087	9,437	14,679
After Diagnosis	17,513	12,479	39,843	20,942	17,588
Treatment	4,326	4,485	26,016	10,686	0
Residential	484	368	9,966	0	0
Outpatient	3,389	2,608	16,050	10,686	0
RX	453	1,509	0	0	0
Non-Treatment	13,186	7,994	13,827	10,256	17,588

Notes: This table reports the mean values of the clinical and spending outcomes (in CPI-U adjusted 2017 constant dollars) for the new diagnosis sample. All patients are included in column 1 (N=78,222). Columns 2-5 subdivide the sample into four groups: column 2 includes patients who received medication-assisted treatment, column 3 includes patients who received residential treatment that did not include the use of medications, column 4 includes patients who received treatment without residential services or medication, and column 5 includes patients who did not receive any form of treatment. Clinical outcomes are expressed as the percentage of patients observed with any of the listed events in the six months following diagnosis. Spending is computed as total allowed amounts in the six months before or after the diagnosis. Details on how events and spending categories are defined are available in Appendix A.

Table 2: **Effect of small-group parity on treatment utilization**

	(1) Any		(2) MAT		(3) Med-free Res		(4) Med-free OP	
Small Group × Post	-0.009	[0.012]	-0.027**	[0.011]	0.014***	[0.005]	0.005	[0.010]
Small Group	0.025***	[0.008]	0.029***	[0.007]	0.000	[0.003]	-0.004	[0.006]
Female	-0.075***	[0.006]	-0.051***	[0.006]	-0.001	[0.002]	-0.023***	[0.005]
Age 25-34	-0.071***	[0.010]	0.077***	[0.009]	-0.030***	[0.004]	-0.117***	[0.008]
Age 35-44	-0.181***	[0.010]	-0.004	[0.009]	-0.046***	[0.004]	-0.131***	[0.008]
Age 45-54	-0.298***	[0.009]	-0.088***	[0.009]	-0.049***	[0.004]	-0.162***	[0.008]
Age 55-64	-0.385***	[0.010]	-0.135***	[0.010]	-0.060***	[0.004]	-0.190***	[0.008]
Employee	0.018***	[0.007]	0.067***	[0.006]	-0.015***	[0.003]	-0.034***	[0.006]
POS	0.021***	[0.007]	-0.008	[0.007]	0.025***	[0.003]	0.004	[0.006]
PPO	0.048***	[0.010]	0.029***	[0.010]	-0.006	[0.004]	0.026***	[0.008]
CDHP	-0.009	[0.008]	-0.018**	[0.008]	-0.002	[0.003]	0.011*	[0.007]
Constant	0.695***	[0.008]	0.309***	[0.008]	0.067***	[0.003]	0.319***	[0.007]
State-Year FEs	Yes		Yes		Yes		Yes	
Depvar Mean	0.53		0.31		0.04		0.18	
Adj R^2	0.12		0.08		0.04		0.05	
Obs	28325		28325		28325		28325	

Notes: This table reports OLS regression estimates of equation (1) in the text using the sample of newly diagnosed, fully-insured enrollees between 2010 and 2017 who were not diagnosed in the second half of 2013. The independent variable of interest is an indicator for being covered in a small-group plan after parity was passed. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are reported in brackets. Significance: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 3: **Relationship between clinical outcomes and small-group parity**

	(1) Overdose		(2) Drug-related ER		(3) Other ER	
Small Group × Post	0.003	[0.005]	0.010	[0.011]	0.002	[0.010]
Small Group	-0.002	[0.003]	-0.016**	[0.007]	-0.030***	[0.007]
Female	0.005*	[0.003]	0.032***	[0.006]	0.085***	[0.005]
Age 25-34	-0.023***	[0.004]	-0.060***	[0.009]	0.039***	[0.008]
Age 35-44	-0.030***	[0.004]	-0.075***	[0.009]	0.044***	[0.008]
Age 45-54	-0.023***	[0.004]	-0.065***	[0.009]	0.056***	[0.008]
Age 55-64	-0.023***	[0.005]	-0.065***	[0.010]	0.065***	[0.009]
Employee	-0.016***	[0.003]	-0.061***	[0.006]	-0.058***	[0.006]
POS	-0.000	[0.003]	0.001	[0.006]	-0.006	[0.006]
PPO	-0.002	[0.004]	-0.024**	[0.010]	0.008	[0.009]
CDHP	0.005	[0.004]	0.020**	[0.008]	0.013*	[0.007]
Constant	0.069***	[0.004]	0.330***	[0.008]	0.184***	[0.007]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	0.04		0.25		0.21	
Adj R^2	0.01		0.02		0.03	
Obs	28325		28325		28325	

Notes: This table reports OLS regression estimates of equation (1) in the text using the sample of newly diagnosed, fully-insured enrollees between 2010 and 2017 who were not diagnosed in the second half of 2013. The independent variable of interest is an indicator for being covered in a small-group plan after parity was passed. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are reported in brackets. Significance: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 4: **Relationship between spending outcomes and small-group parity**

	(1) Ln(TX Spend)		(2) Ln(Non-TX Spend)		(3) Ln(Total Spend)	
Small Group × Post	-0.025	[0.098]	-0.030	[0.071]	0.005	[0.044]
Small Group	0.130**	[0.064]	-0.101**	[0.047]	-0.084***	[0.029]
Female	-0.594***	[0.050]	0.832***	[0.036]	0.373***	[0.022]
Age 25-34	-0.740***	[0.079]	0.137**	[0.058]	0.067*	[0.035]
Age 35-44	-1.685***	[0.079]	0.812***	[0.058]	0.227***	[0.035]
Age 45-54	-2.555***	[0.077]	1.446***	[0.057]	0.422***	[0.035]
Age 55-64	-3.272***	[0.086]	2.017***	[0.063]	0.679***	[0.039]
Employee	0.059	[0.056]	-0.543***	[0.041]	-0.386***	[0.025]
POS	0.334***	[0.058]	0.102**	[0.042]	0.167***	[0.026]
PPO	0.546***	[0.086]	0.027	[0.063]	0.196***	[0.038]
CDHP	-0.054	[0.069]	-0.053	[0.051]	-0.055*	[0.031]
Constant	5.513***	[0.068]	6.298***	[0.050]	8.142***	[0.031]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	4.07		7.15		8.41	
Adj R^2	0.12		0.20		0.16	
Obs	28325		28325		28325	

Notes: This table reports OLS regression estimates of equation (1) in the text using the sample of newly diagnosed, fully-insured enrollees between 2010 and 2017 who were not diagnosed in the second half of 2013. The independent variable of interest is an indicator for being covered in a small-group plan after parity was passed. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are reported in brackets. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: **Relationship between county-level access to waivered providers and OUD treatment utilization**

	(1) Any		(2) MAT		(3) Med-free Res		(4) Med-free OP	
BP MD Share$_{ct}$	0.040	[0.056]	0.167***	[0.050]	-0.036	[0.023]	-0.092**	[0.040]
BP MD Share$_{c,2008}$	0.181*	[0.095]	0.109	[0.090]	0.020	[0.032]	0.053	[0.059]
Female	-0.077***	[0.004]	-0.057***	[0.003]	-0.004***	[0.001]	-0.016***	[0.003]
Age 25-34	-0.077***	[0.006]	0.071***	[0.006]	-0.032***	[0.003]	-0.117***	[0.005]
Age 35-44	-0.184***	[0.006]	-0.010*	[0.006]	-0.041***	[0.002]	-0.134***	[0.005]
Age 45-54	-0.302***	[0.006]	-0.092***	[0.005]	-0.046***	[0.002]	-0.164***	[0.005]
Age 55-64	-0.390***	[0.006]	-0.144***	[0.005]	-0.055***	[0.003]	-0.192***	[0.005]
Employee	0.020***	[0.004]	0.047***	[0.004]	-0.010***	[0.001]	-0.016***	[0.003]
POS	0.010**	[0.005]	-0.008*	[0.004]	0.011***	[0.002]	0.007***	[0.004]
PPO	0.019**	[0.007]	0.012*	[0.006]	-0.023***	[0.003]	0.014**	[0.006]
CDHP	-0.010**	[0.005]	-0.022***	[0.004]	0.002	[0.002]	0.010**	[0.004]
Ln(AvgSpend$_{ct}$)	0.008	[0.015]	0.035***	[0.014]	0.004	[0.005]	-0.033***	[0.011]
Unemp Rate$_{ct}$	-0.007***	[0.002]	-0.001	[0.002]	-0.000	[0.001]	-0.006***	[0.001]
Constant	0.694***	[0.118]	0.041	[0.111]	0.058	[0.040]	0.624***	[0.088]
State-Year FEs	Yes		Yes		Yes		Yes	
Depvar Mean	0.53		0.30		0.04		0.19	
Adj R^2	0.13		0.08		0.03		0.05	
Obs	78222		78222		78222		78222	

Notes: This table reports OLS regression estimates of equation (3) in the text using the sample of newly diagnosed patients between 2009 and 2017. The independent variable is *BP MD Share*, the ratio of the number of practitioners with waivers to prescribe buprenorphine to the number of PCPs and psychiatrists in a county in that year. The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c, as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets. Significance: $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 6: **Relationship between county-level access to waivered providers and OUD patient clinical outcomes**

	(1) Overdose		(2) Drug-related ER		(3) Other ER	
BP MD Share$_{ct}$	0.024	[0.021]	-0.107**	[0.049]	-0.012	[0.044]
BP MD Share$_{c,2008}$	-0.049	[0.032]	-0.014	[0.077]	0.065	[0.074]
Female	0.009***	[0.002]	0.031***	[0.003]	0.086***	[0.003]
Age 25-34	-0.029***	[0.003]	-0.066***	[0.005]	0.050***	[0.005]
Age 35-44	-0.033***	[0.003]	-0.080***	[0.005]	0.061***	[0.005]
Age 45-54	-0.028***	[0.003]	-0.068***	[0.005]	0.059***	[0.005]
Age 55-64	-0.027***	[0.003]	-0.077***	[0.006]	0.067***	[0.006]
Employee	-0.013***	[0.002]	-0.066***	[0.004]	-0.066***	[0.003]
POS	-0.001	[0.002]	-0.004	[0.004]	0.000	[0.004]
PPO	-0.000	[0.003]	-0.013**	[0.006]	0.011	[0.006]
CDHP	0.001	[0.002]	0.008*	[0.004]	0.006	[0.004]
Ln(AvgSpend$_{ct}$)	0.011*	[0.006]	0.015	[0.012]	0.026**	[0.012]
Unemp Rate$_{ct}$	-0.001	[0.001]	0.001	[0.001]	0.002	[0.001]
Constant	-0.012	[0.045]	0.209**	[0.100]	-0.049	[0.093]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	0.05		0.26		0.23	
Adj. R^2	0.01		0.03		0.02	
Obs	78222		78222		78222	

Notes: This table reports OLS regression estimates of equation (3) in the text using the sample of newly diagnosed patients between 2009 and 2017. The independent variable is *BP MD Share*, the ratio of the number of practitioners with waivers to prescribe buprenorphine to the number of PCPs and psychiatrists in a county in that year. The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c, as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets. Significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: **Relationship between county-level access to waivered providers and OUD post-diagnosis spending**

	(1) Ln(TX Spend)		(2) Ln(Non-TX Spend)		(3) Ln(Total Spend)	
BP MD Share$_{ct}$	0.141	[0.465]	-0.558	[0.347]	-0.168	[0.215]
BP MD Share$_{c,2008}$	1.676**	[0.780]	-0.249	[0.533]	0.047	[0.320]
Female	-0.607***	[0.029]	0.846***	[0.020]	0.356***	[0.013]
Age 25-34	-0.821***	[0.050]	0.220***	[0.037]	0.076***	[0.023]
Age 35-44	-1.701***	[0.050]	0.950***	[0.037]	0.295***	[0.022]
Age 45-54	-2.626***	[0.049]	1.526***	[0.035]	0.472***	[0.022]
Age 55-64	-3.363***	[0.053]	2.018***	[0.038]	0.664***	[0.023]
Employee	0.099***	[0.032]	-0.538***	[0.022]	-0.373***	[0.013]
POS	0.239***	[0.037]	0.171***	[0.027]	0.195***	[0.017]
PPO	0.286***	[0.055]	0.166***	[0.040]	0.199***	[0.024]
CDHP	-0.078*	[0.040]	-0.003	[0.029]	-0.027	[0.018]
Ln(AvgSpend$_{ct}$)	0.178	[0.121]	0.184**	[0.078]	0.246***	[0.049]
Unemp Rate$_{ct}$	-0.076***	[0.013]	-0.059***	[0.009]	-0.051***	[0.005]
Constant	4.691***	[0.980]	5.261***	[0.626]	6.532***	[0.397]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	4.08		7.39		8.56	
Adj R^2	0.12		0.19		0.15	
Obs	78222		78222		78222	

Notes: This table reports OLS regression estimates of equation (3) in the text using the sample of newly diagnosed patients between 2009 and 2017. The dependent variables are ln(spending measure + 1). The independent variable is *BP MD Share*, the ratio of the number of practitioners with waivers to prescribe buprenorphine to the number of PCPs and psychiatrists in a county in that year. The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c, as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets. Significance: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 8: **Relationship between OUD treatment utilization and county-level access to waivered providers, above and below national median share**

	(1) Any		(2) MAT		(3) Med-free Res		(4) Med-free OP	
BP MD Share$_{ct}$								
× BP Share Below Med$_{ct}$	0.380***	[0.145]	0.389***	[0.137]	0.032	[0.054]	-0.041	[0.109]
× BP Share Above Med$_{ct}$	-0.007	[0.059]	0.110**	[0.052]	-0.037	[0.024]	-0.081*	[0.044]
BP Share Above Med$_{ct}$	0.026***	[0.010]	0.026***	[0.009]	0.003	[0.003]	-0.002	[0.007]
BP MD Share$_{c,2008}$	0.169*	[0.094]	0.098	[0.088]	0.018	[0.032]	0.053	[0.059]
Female	-0.077***	[0.004]	-0.057***	[0.003]	-0.004***	[0.001]	-0.016***	[0.003]
Age 25-34	-0.077***	[0.006]	0.072***	[0.006]	-0.032***	[0.003]	-0.117***	[0.005]
Age 35-44	-0.184***	[0.006]	-0.009*	[0.006]	-0.041***	[0.002]	-0.134***	[0.005]
Age 45-54	-0.302***	[0.006]	-0.092***	[0.005]	-0.046***	[0.002]	-0.164***	[0.005]
Age 55-64	-0.390***	[0.006]	-0.144***	[0.005]	-0.055***	[0.003]	-0.192***	[0.005]
Employee	0.020***	[0.004]	0.047***	[0.004]	-0.010***	[0.001]	-0.016***	[0.003]
POS	0.010**	[0.005]	-0.008*	[0.004]	0.011***	[0.002]	0.007*	[0.004]
PPO	0.019**	[0.007]	0.012**	[0.006]	-0.007***	[0.002]	0.014**	[0.006]
CDHP	-0.010**	[0.005]	-0.022***	[0.004]	0.002	[0.002]	0.010**	[0.004]
Ln(AvgSpend$_{ct}$)	0.012	[0.015]	0.038***	[0.014]	0.006	[0.005]	-0.032***	[0.011]
Unemp Rate$_{ct}$	-0.007***	[0.002]	-0.001	[0.002]	-0.000	[0.001]	-0.006***	[0.004]
Constant	0.641***	[0.119]	0.002	[0.111]	0.021	[0.041]	0.618***	[0.089]
State-Year FEs	Yes		Yes		Yes		Yes	
Depvar Mean	0.53		0.30		0.04		0.19	
Adj R^2	0.13		0.08		0.03		0.05	
Obs	78222		78222		78222		78222	

Notes: This table re-estimates equation (3), where the independent variable BP MD Share$_{ct}$ is interacted with indicator variables for BP MD Share$_{ct}$ being below or above the national county median across all years in the sample (population-weighted). The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets. Significance: $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 9: **Relationship between clinical outcomes and county-level access to waivered providers, above and below national median share**

	(1) Overdose		(2) Drug-related ER		(3) Other ER	
BP MD Share$_{ct}$						
× BP Share Below Med$_{ct}$	0.015	[0.057]	-0.320**	[0.132]	-0.392***	[0.125]
× BP Share Above Med$_{ct}$	0.024	[0.023]	-0.075	[0.051]	0.023	[0.047]
BP Share Above Med$_{ct}$	-0.000	[0.004]	-0.017**	[0.008]	-0.023***	[0.008]
BP MD Share$_{c,2008}$	-0.049	[0.031]	-0.006	[0.077]	0.077	[0.074]
Female	0.009***	[0.002]	0.031***	[0.003]	0.086***	[0.003]
Age 25-34	-0.029***	[0.003]	-0.066***	[0.005]	0.050***	[0.005]
Age 35-44	-0.033***	[0.003]	-0.080***	[0.005]	0.061***	[0.005]
Age 45-54	-0.028***	[0.003]	-0.068***	[0.005]	0.059***	[0.005]
Age 55-64	-0.027***	[0.002]	-0.077***	[0.005]	0.0667***	[0.006]
Employee	-0.013***	[0.002]	-0.066***	[0.006]	-0.066***	[0.003]
POS	-0.001	[0.00]	-0.004**	[0.004]	0.000	[0.004]
PPO	-0.000	[0.002]	-0.013***	[0.006]	0.011**	[0.006]
CDHP	0.001	[0.003]	0.008*	[0.004	0.006	[0.004]
Ln(AvgSpend$_{ct}$)	0.011*	[0.006]	0.013	[0.012]	0.021*	[0.012]
Unemp Rate$_{ct}$	-0.001	[0.001]	0.001	[0.001]	0.001	[0.001]
Constant	-0.011	[0.047]	0.244***	[0.102]	0.010	[0.094]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	0.05		0.26		0.23	
Adj R^2	0.01		0.03		0.02	
Obs	78222		78222		78222	

Notes: This table re-estimates equation (3), where the independent variable BP MD Share$_{ct}$ is interacted with indicator variables for BP MD Share$_{ct}$ being below or above the national county median across all years in the sample (population-weighted). The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets.

Table 10: **Relationship between post-diagnosis spending and county-level access to waivered providers, above and below national median share**

	(1) Ln(TX Spend)		(2) Ln(Non-TX Spend)		(3) Ln(Total Spend)	
BP MD Share$_{ct}$						
× BP Share Below Med$_{ct}$	3.038**	[1.194]	-0.554	[0.791]	0.187	[0.488]
× BP Share Above Med$_{ct}$	-0.230	[0.495]	-0.436	[0.374]	-0.169	[0.232]
BP Share Above Med$_{ct}$	0.210***	[0.078]	-0.040	[0.052]	0.011	[0.031]
BP MD Share$_{c,2008}$	1.572**	[0.760]	-0.225	[0.527]	0.039	[0.319]
Female	-0.607***	[0.029]	0.846***	[0.020]	0.356***	[0.013]
Age 25-34	-0.821***	[0.050]	0.220***	[0.037]	0.076***	[0.023]
Age 35-44	-1.700***	[0.050]	0.950***	[0.037]	0.295***	[0.022]
Age 45-54	-2.624***	[0.049]	1.526***	[0.035]	0.472***	[0.022]
Age 55-64	-3.362***	[0.053]	2.018***	[0.038]	0.665***	[0.023]
Employee	0.098***	[0.032]	-0.538***	[0.022]	-0.373***	[0.013]
POS	0.240***	[0.037]	0.171***	[0.027]	0.195***	[0.017]
PPO	0.287***	[0.055]	0.165***	[0.040]	0.199***	[0.024]
CDHP	-0.077*	[0.040]	-0.003	[0.029]	-0.027	[0.018]
Ln(AvgSpend$_{ct}$)	0.212*	[0.121]	0.184**	[0.078]	0.250***	[0.049]
Unemp Rate$_{ct}$	-0.070***	[0.013]	-0.050***	[0.009]	-0.050***	[0.005]
Constant	4.257***	[0.992]	5.278***	[0.38]	6.481***	[0.402]
State-Year FEs	Yes		Yes		Yes	
Depvar Mean	4.08		7.39		8.56	
Adj R^2	0.12		0.19		0.15	
Obs	78222		78222		78222	

Notes: This table re-estimates equation (3), where the independent variables BP MD Share$_{ct}$ interacted with indicator variables for BP MD Share$_{ct}$ being below or above the national county median across all years in the sample (population-weighted). The unit of observation is a patient i who received a "new" diagnosis of OUD in year t while living in county c as described in the text. Except where noted, control variables vary at the patient level. Omitted categories are age 18-24 and EPO/HMO plan type. Standard errors are clustered at the county-year level and reported in brackets.