Appalachian State University

Department of Economics Working Paper

Number 23-08 | September 2023

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Impacts of Certificate-of-need State Laws on Substance Abuse Treatment Facilities and Services

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Abstract

We investigate how the Certificate-of-need laws influence access to substance abuse treatment facilities in the United States. First, we use the National Directory of Drug and Alcohol Abuse Treatment Facilities dataset, which lists all federal, state, and local government facilities and private facilities that provide substance abuse treatment services in 2020. We also use Geocodio, a geocoding tool, to determine the precise locations of these facilities. Next, we develop a novel access index that accounts for both driving distance and travel time to measure the ease of reaching these facilities for individuals living at the population-weighted county centroids. Our findings indicate that counties located in states with Certificate-of-need laws have 10% lower access to substance abuse treatment services compared to their neighboring counties in states without such regulations.

Keywords: Certificate-of-need laws, Substance abuse treatment services, Spatial accessibility
JEL Classification:

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1 Introduction

Certificate-of-need laws require certain healthcare facilities to obtain approval from a state regulatory agency before undertaking significant capital expenditures or expanding their service capacity, such as building new facilities or purchasing expensive medical equipment. These laws aim to regulate the supply and distribution of healthcare resources and prevent wasteful duplication or overinvestment in healthcare facilities. However, critics argue that Certificate-of-need laws are anti-competitive, increase healthcare costs, reduce access to care, quality of care, and impede innovation (State Policy Network, 2021; Pitsor and Parham, 2022; Moffit, 2022).

In this article, we aim to provide quantitative evidence of how the Certificate-of-need law affects access to care. Our motivation is to address the debate surrounding Certificate-of-need laws, which aim to regulate the supply and distribution of healthcare resources to prevent wasteful duplication and overinvestment, while critics argue that they create barriers to entry and expansion for providers, resulting in limited availability and accessibility of treatment facilities and services. Specifically, we will examine the relationship between Certificate-of-need laws and the availability and accessibility of substance use treatment centers. However, there is little empirical evidence on the impact of Certificate-of-need laws on substance use treatment facilities and whether they achieve their intended objectives of ensuring an adequate supply.

Some states modified or repealed their Certificate-of-need laws for substance use disorder (SUD) treatment facilities to meet the increased demand for SUD services during the COVID-19 pandemic. However, some states still require providers to demonstrate economic necessity before opening or expanding. Bailey et al. (2022) found mixed results when analyzing the impact of state-level Certificate-of-need laws using data from 2002 to 2019. Their findings suggest that while Certificate-of-need laws are associated with a decreased likelihood of facilities accepting private insurance, there is no statistically significant effect on the number of facilities, beds, or clients, nor is there a significant impact on the acceptance of Medicare.

We improve the Bailey et al. (2022) by providing a more granular approach. Bailey et al. (2022) used the Substance Abuse and Mental Health Services Administration's (SAMHSA's) National Survey of Substance Abuse Treatment Services (N-SSATS) data to count the number of facilities by state. Instead of simply counting the number of facilities, we will redefine the meaning and interpretation of spatial access to substance use treatment facilities.

We utilize the National Directory of Drug And Alcohol Abuse Treatment Facilities, maintained by the Substance Abuse and Mental Health Services Administration (SAMHSA). The dataset includes a comprehensive list of substance use treatment facilities for 2020, encompassing federal, state, local government, and private establishments. In addition, the data provide complete lists of substance use treatment facilities, including their respective services and locations.

We convert the location data into longitude and latitude coordinates, enabling the development of a novel spatial access index for each county's population-weighted centroid. This index is computed as the sum of the inverse distance, adjusted for travel impedance and the facility's catchment. A facility's catchment refers to the area within a specific distance from a healthcare facility that potentially utilizes its services (Tao et al., 2018). Furthermore, the data includes a list of services each substance abuse treatment facility provides. We develop a county-level access index for the facilities and various services, such as buprenorphine, methadone, naltrexone, federally-certified opioid treatment programs, Medication-Assisted Treatment (MAT), and others.

The National Directory of Drug And Alcohol Abuse Treatment Facilities dataset, released by SAMHSA in June 2022, provides information specifically for 2020, making it a cross-sectional dataset. We adopt a regression framework similar to canonical difference-in-differences, but in our case, we replace the time dimension with a border identifier, given the cross-sectional nature of our dataset. By adopting this approach, we can compare the disparity in access to substance use treatment facilities between border counties in states with Certificate-of-need laws and those without while accounting for unobservable factors that might affect access in both border and non-border counties across states that have passed or not enacted Certificate-of-need laws. To enable a more intuitive comparison, such as percentage change (Bellemare and Wichman, 2020), we apply the inverse hyperbolic sine transformation to our access index and employ regression models using an arcsinh–linear specification.

We find counties with Certificate-of-need laws enacting states that border the counties without such laws have nearly 10% less spatial accessibility to substance use treatment facilities at a 5% level of significance. We provide robustness checks based on bootstrapping, randomization inference, and multiple regression with covariates. Our analysis is highly relevant, especially in policy, because SUDs are preventable and treatable. Treatment reduces SUDs and their harms, but a treatment gap persists. Lack of treatment providers or programs is a common barrier to services (Center for Behavioral Health Statistics and Quality, 2019).

Our results have important policy implications, particularly in light of the ongoing opioid epidemic in the United States. By understanding the effects of Certificate-of-need laws on access to substance use treatment facilities, policymakers can make more informed decisions about how to address the opioid crisis and ensure that individuals who need treatment have access to it.

Section 2 reviews the literature on Certificate-of-need laws and spatial access to healthcare. We then detail the data utilized for our analysis in Section 3, followed by an explanation of our methodology in Section 4. In Sections 5 and 6, we present and discuss our results with implications and limitations and conclude the study in Section 7.

2 Literature

2.1 Certificate-of-need laws

The effects of Certificate-of-need laws on health outcomes and costs have been well-researched. However, few studies have examined the impact of Certificate-of-need laws on treatment for substance use disorders (SUD). Certificate-of-need laws aim to reduce costs associated with providing health services, and research has found mixed results.

Economic theory would predict that a supply-side restriction on entry into a market would cause a leftward shift in the supply curve resulting from the increased cost of production (Bailey, 2018). Moreover, the cost of opening a new firm is further increased by legal and regulatory barriers, such as the requirement to prove "economic necessity."

The impact of Certificate-of-need laws on health services can be challenging due to the heterogeneous nature of these laws across states. In addition, variations in restricted services and types of cost-increase limitations make assessing the policy's effects difficult. Economic theory suggests that the Certificate-of-need law will reduce costs if a health service has elastic demand. However, for an inelastic demand curve, the policy would fail to reduce costs and could lead to cost increases (Bailey, 2018). Substance use treatment is estimated to have an inelastic demand curve, which suggests that states with Certificate-of-need laws for substance use treatment may not achieve their intended cost-reducing effects (Bishai et al., 2008).

Little research has been done on this relationship outside of a study that measures Certificate-of-need laws' effects on access to substance use treatment using beds per capita as their measure of access (Bailey et al., 2022). While they find no statistically significant impact on beds or facilities, Certificate-of-need laws reduce private insurance acceptance by about 6%. Alternatively, Mitchell and Stratmann (2022) find that during the COVID-19 pandemic, hospitals in states with Certificate-of-need laws were more likely to run out of beds and had more days with bed usage greater than 70%. More closely related to substance use treatment, Certificate-of-need laws were associated with fewer psychiatric hospitals and reduced acceptance of Medicare for psychiatric services (Bailey and Lewin, 2021).

Perhaps the largest body of evidence on the effects of Certificate-of-need laws is the impact on the accessibility of services. States with Certificate-of-need laws have fewer providers, reduced number of hospital beds, and reduced rural access to care (Baker and Stratmann, 2021; Hellinger, 2009; Stratmann and Koopman, 2016). Reductions in the number of providers are a major concern for the accessibility of care. States that implement Certificate-of-Need laws show a 20-33% reduction in healthcare providers, and patients are more likely to travel outside their home county to access services (Baker and Stratmann, 2021). This leads to substituting cheaper non-hospital-based care with more expensive hospital-based services, as hospitals are protected from competition under the Certificate-of-Need laws Baker and Stratmann (2021). Reductions in the number of hospital beds are estimated to be about 10% for states with Certificate-of-need laws. This reduction in beds is predicted to affect healthcare expenditures indirectly. However, this may result from reduced services (Hellinger, 2009). Rural access to care is a commonly cited reason for the disparities in health outcomes between rural and urban populations. Certificate-of-Need laws significantly affect rural care, as it can be more challenging to demonstrate the need for healthcare in rural and spread-out regions. (Stratmann and Koopman, 2016) finds that Certificate-of-need laws negatively impact this rural access.

Certificate-of-need laws affect populations differently, as each state has its version of the regulation. For example, some states limit major hospital expansions while others restrict specific imaging services such as MRI, CT, or PET (Kim et al., 2016). The main goal of Certificate-of-need laws is to limit spending; however, evidence shows no reduction in the usage rates of services in states with these laws (Kim et al., 2016). Certificate-of-need laws limit investment in these services, leading to alternative service methods. For example, mobile MRI scanners have been used in some states to reduce costs slightly (by approximately $400), although this occurs because of the reduced usage of services by patients who may need them. (Perry, 2017).

Access to substance use treatment is the best chance of success for users to live abstinence-based lifestyles (Swensen, 2015; Amiri et al., 2018; Condelli and Hubbard, 1994; Beardsley et al., 2003). Living close to treatment facilities is crucial for success, with patients living within a mile of the facility having higher rates of success and longer lengths of stay (Amiri et al., 2018; Corredor-Waldron and Currie, 2022). These positive outcomes, including abstinence, reduced criminal activity, and employment, are associated with sustained positive outcomes (Beardsley et al., 2003; Corredor-Waldron and Currie, 2022). This is especially true for outpatient treatment, where patients must travel to and from the facility, and distance can significantly impact success. To further explore the relationship between access to treatment facilities and treatment outcomes, we investigate the impact of supply-side restrictions on expansion resulting from Certificate-of-need laws within a state.

Supply-side regulations are predicted to reduce supply in a market, thus leading to lower quantities supplied at all prices. This theoretical framework has allowed researchers to test this theory when health supply is restricted through Certificate-of-need law regulations. For instance, Certificate-of-need laws have been shown to reduce access to imaging services, according to a study by Baker and Stratmann (2021). This may be because established firms in a county are more likely to receive favorable outcomes when seeking approval for expansions. Moreover, Chiu (2021) reports that states with Certificate-of-need laws experience higher rates of cardiac arrest-related mortality than their cross-border counties without Certificate-of-need law restrictions, possibly due to limited access to emergency care services.

Regarding health care quality, Certificate-of-need laws have little effect on quality measures. This could be due to the labor substitution from registered and licensed practical nurses towards certified nursing assistants (Fayissa et al., 2020). Conover and Bailey (2020) provide a review of the literature on Certificate-of-need laws and find that the results on access are still mixed; however, most studies find a negative relationship between Certificate-of-need laws and access measures. We add to this literature by determining the impact of Certificate-of-need laws on spatial access to substance use treatment services.

Certificate-of-need laws have been shown to impact competition, showing that states with Certificate-of-need laws see less market entry by nonhospital and new hospital providers (Baker and Stratmann, 2021). Investment into new technology and efficiency measures in the provision of health care is also impacted by the existence of Certificate-of-need laws. Conover and Sloan (1998) finds that investment in these areas is reduced in acute care spending areas with more mature Certificate-of-need laws but does not necessarily lead to reductions in per capita health care spending (Conover and Sloan, 1998).

2.2 Spatial access to medical services

Health care accessibility is the ease with which individuals access and utilize health care services (Penchansky and Thomas, 1981). Spatial accessibility includes these accessibility measures relative to geographic space (Luo and Wang, 2003). According to Wang (2012), spatial accessibility to health care services increases as the proximity to a facility decreases. In addition, studies have demonstrated that spatial accessibility to health care services is associated with better patient outcomes and can indicate barriers to medical access (He et al., 2022; McGrail, 2012; Luo and Qi, 2009; Wang and Luo, 2005; Guagliardo, 2004; Luo and Wang, 2003). This issue mainly affects rural communities as they often experience longer travel and increased distance to medical facilities (MacEwan et al., 2022; Wang, 2012; McGrail and Humphreys, 2009; Joseph and Bantock, 1982).

The two-step floating catchment area (2SFCA) method takes population-weighted centroids and creates an access measure that accounts for population demand, distance to facilities, and driving duration (McCrum et al., 2022; Zhang et al., 2022; Yang et al., 2006). This method accounts for the cross-border travel behavior when individuals' nearest facility is not located within their administrative area. For example, a person may have to travel outside their county of residence to receive specialty care which would not be captured using a simple population demand model, which uses a count-based measure of access.

McCrum et al. (2022) employs this method to analyze the spatial accessibility of emergency surgical services within the US and finds that approximately 1 in 10 residents face low accessibility. This indicates that geographic barriers are an essential measure of access, especially in cases of time-sensitive care. Yang et al. (2006) compares the use of the 2SFCA to a kernel density method and concludes that the former creates a better measure of access that captures travel behavior more precisely than the latter. It is essential, however, to understand the limitations of these methods in how they measure access.

Measuring access using driving distance and driving time to the nearest facility does not account for the availability of services or the capacity of the facility to provide needed services (McGrail and Humphreys, 2009). It is simply a measure of proximity. This proximity identification is essential for the analysis and the environment for which it is employed. It is supported when proximity to a facility is necessary for successful outcomes. Proximity to substance use treatment is essential in determining accessibility. Many services (i.e., outpatient, medication-assisted treatment, counseling, etc.) require regular travel to and from the facility to receive care.

3 Data

3.1 National Directory of Drug and Alcohol Abuse Treatment Facilities

We gather The National Directory of Drug and Alcohol Abuse Treatment Facilities for 2022.[1] This dataset lists federal, state, and local government and private facilities providing substance abuse treatment services in the United States for 2020 along with their

[1] https://www.samhsa.gov/data/report/national-directory-of-drug-and-alcohol-abuse-treatment-facilitie

location. We used the Geocodio website to convert location to respective latitude and longitude.[2]

The National Directory of Drug and Alcohol Abuse Treatment Facilities for 2022 also allows for differentiation among types of care, service setting, opioid medications used in treatment, variety of opioid treatment, treatment approaches, facility operation, license/certification/accreditation, payment assistance available, and payment acceptance methods. For our research, we only focused on all the types of opioid-related treatment centers. We identified 12,018 unique opioid-related treatment facilities within the US. These centers offer one or more of the opioid-related treatment services listed in Table 1, and the counts of facilities offering each service are included. As a treatment center may provide multiple services there for the sum of the numbers of facilities in Table 1 is more significant than 12,018.

Table 1: Types of services rendered by substance abuse treatment facility, 2020

Service names	Numbers of facility
Accepts clients using MAT but prescribed elsewhere	6868
Prescribes buprenorphine	4860
Prescribes naltrexone	4669
Buprenorphine maintenance	4420
Relapse prevention with naltrexone	3892
Buprenorphine maintenance for predetermined time	3012
Buprenorphine detoxification	2131
Federally-certified Opioid Treatment Program	1499
Methadone maintenance	1381
Lofexidine/clonidine detoxification	1192
Methadone maintenance for predetermined time	1012
Does not treat substance abuse disorders	1002
Does not use MAT for substance abuse disorders	654
Methadone detoxification	595
Use methadone/buprenorphine for pain management or emergency dosing	159

Notes: National Directory of Drug and Alcohol Abuse Treatment Facilities dataset identified 12,018 unique opioid-related treatment facilities within the US in 2020. Each location may offer one or more opioid-related treatment services.

[2] https://www.geocod.io/

3.2 Certificate-of-need laws

Certificate-of-need laws in most US states require healthcare providers to prove to a state board that their proposed healthcare services should be allowed to open or expand. While Certificate-of-need laws most commonly focus on hospital and nursing home facilities, many states require Certificate-of-need for other healthcare providers and services. As of 2020, 23 US states retain Certificate-of-need laws, requiring providers to prove their "economic necessity," or providers must prove the economic viability and public need for their services before opening or expanding. While the academic literature on how Certificate-of-need laws affect costs and access for hospitals and nursing homes is extensive, there is a need for more comprehensive research on how substance use Certificate-of-need laws impact treatment availability and accessibility.

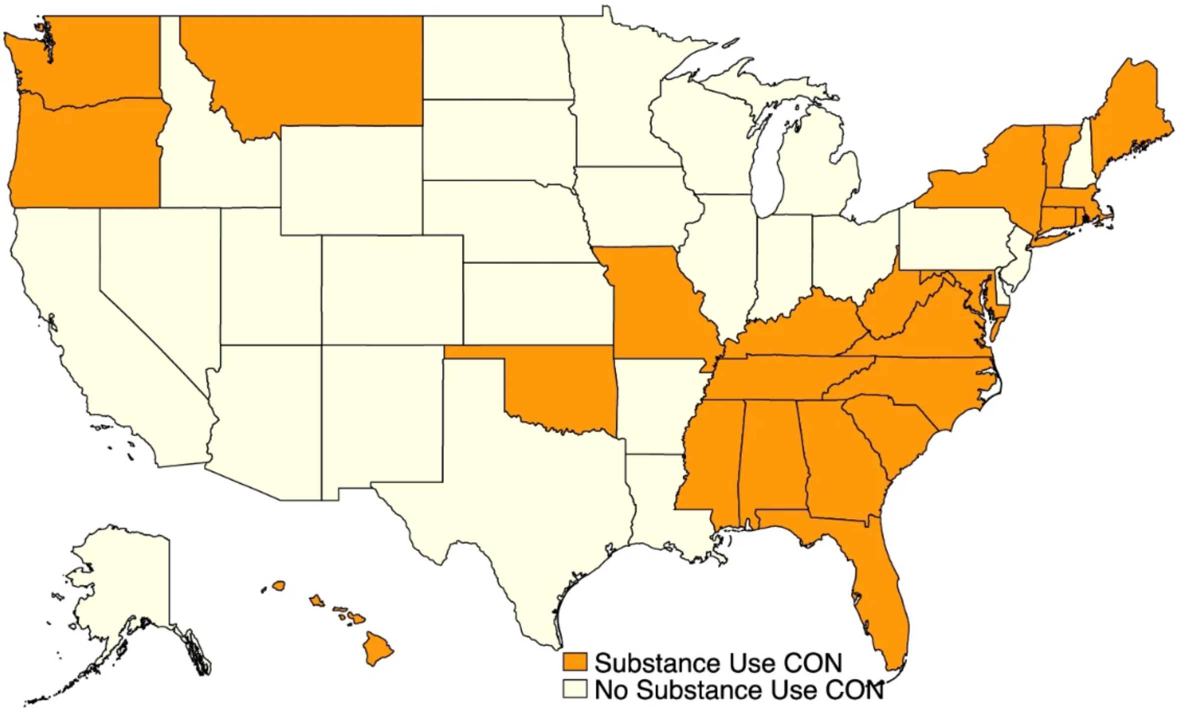
Certificate-of-need law began in New York in 1964 to reduce the rising health care costs (Chiu, 2021; Conover and Bailey, 2020; Bailey, 2018). Following the introduction of Medicare in 1965, hospitals and medical centers underwent substantial expansion. As a result of this increase in investment in expanding services, healthcare costs rose significantly (Chiu, 2021). In 1974, the National Health Planning and Resources Development Act tied federal assistance monies to their implementation, including Medicare and Medicaid (Bailey, 2018). As a result of these requirements, most states implemented their version of Certificate-of-need laws, with Louisiana being the only state to opt out (Bailey, 2018). Louisiana eventually implemented its version of Certificate of Need called Facility Need Review and is often included as a Certificate-of-need law state for analysis purposes. After the requirements for federal money were repealed, 15 states had repealed their Certificate-of-need laws by the 1980s.

Data on Certificate-of-need laws comes from the American Health Planning Association (AHPA)[3] and the Mercatus Center.[4] Figure 1 displays the states with Certificate-of-need laws as of 2020, which comprises states of AL, CT, FL, GA, HI, KY, ME, MD,

[3] https://www.mercatus.org/publications/healthcare/con-laws-2020-about-update

[4] https://www.ncsl.org/health/certificate-of-need-state-laws

Figure 1: Certificate-of-need laws and substance abuse treatment



Source: Bailey et al. (2022)

MA, MS, MO, MT, NY, NC, OK, OR, RI, SC, TN, VT, VA, WA, WV, and DC.

3.3 Population weighted centroids at county levels

Populated county areas in the United States are typically not located near the geographic center. This creates significant discrepancies between population-weighted and geometric centroids. This mismatch is particularly evident in western states with large, sparsely populated counties. For instance, in San Bernardino County, California, the geometric center is about 8 miles north of Ludlow, an unincorporated community of 40 people in the Mojave Desert. In contrast, the largest city in the county, San Bernardino, is 80 miles away from Ludlow, in the southwest corner of the county. Therefore, population-weighted centroids are an alternative to geometric centroids and tackle this issue better. While geographic size is a primary factor in the difference between geometric and population-weighted centroids, climate and population factors also contribute significantly. Arid conditions in the western US constrained settlement due to a lack of water, resulting in highly clustered cities. Therefore, population-weighted centroids are one alternative to geometric centroids. We use Dilts (2020) Environmental Systems Research Institute (ESRI) hands-on report of the population-weighted centroid.

3.4 Measure of access

We develop three measures of spatial accessibility to substance use treatment facilities for each county. The first measure is the number of substance use treatment facilities per 100,000 residents in each county, calculated as:

$$\textit{Count based access}_c = \frac{\textit{(numbers of substance abuse treatment facilities)}_c}{\textit{population}_c} \times 100000$$

The second is driving distance by car, and the third is the car driving duration to a facility-based access index. To calculate the second and third measures, we use the Open Source Routing Machine (OSRM) to determine the nearest driving distance (in miles) and duration to the nearest substance abuse treatment facility h from the population-weighted county centroid c.

We use driving distance and duration measures to model the spatial accessibility of each population-weighted county centroid c to substance use treatment facility h for a population of 100,000. We adopt the approach of the modified gravity model proposed by Crooks and Schuurman (2012), which involves summing the inverse of the adjusted distances or durations, taking into account impedance and demand factors.

These supply ratios make intuitive sense, but they have several limitations. For example, they do not account for patients crossing over borders, nor do they consider changes in accessibility within bordered areas. Additionally, they do not explicitly include distance or travel impedance metrics. As a result, the results and interpretations of studies using these ratios can be significantly impacted by the spatial units' size, quantity, and arrangement. Geographers and spatial analysts are familiar with this issue, known as the modifiable areal unit problem (MAUP).

$$Drive\ based\ access_c = \sum_{h=1}^{H} \left(\frac{1}{drive_{c\to h}} \times \theta_{c\to h} \times \frac{1}{V_j} \right)$$

$$Duration\ based\ access_c = \sum_{h=1}^{H} \left(\frac{1}{duration_{c\to h}} \times \phi_{c\to h} \times \frac{1}{U_j} \right)$$

Allowing the gravity type model to consider all the facilitates within the same counties and different counties enable the model of the border crossing behavior. However, to incorporate the impact of travel impedance on accessibility and availability, we define a linear step function penalty parameter for driving distance and duration in a car. This parameter reflects the reduced likelihood of individuals traveling long distances and can be used to model accessibility and availability. For example, a person might travel 35 miles with relative ease. However, they are less inclined to travel from 35 to 70 miles and only if the distance is less than 70. Therefore, we define such a penalty parameter for driving distance in a car.

$$\theta_{c\to h} = \begin{cases} 1 & if\ drive_{c\to h} < 35\ miles \\ \frac{70-\theta_{c\to h}}{70-35} & if\ 35 \le drive_{c\to h} \le 70\ miles \\ 0 & if\ drive_{c\to h} > 70\ miles \end{cases}$$

The penalty parameter for the driving duration is also defined similarly, reflecting the reduced likelihood of individuals traveling longer durations. We assume a person drives up to 30 minutes with ease. Driving becomes more tedious between 30 minutes to 90 minutes. Finally, the person may be unwilling to drive beyond 90 minutes to see a mental health care provider.

$$\phi_{c\to h} = \begin{cases} 1 & if\ duration_{c\to h} < 30\ minutes \\ \frac{90-\phi_{c\to h}}{90-30} & if\ 30 \le duration_{c\to h} \le 90\ minutes \\ 0 & if\ duration_{c\to h} > 90\ minutes \end{cases}$$

We account for differential demand on provider facilities in surrounding areas using the solution proposed by Joseph and Bantock (1982). We augment a population demand adjustment factor, V_j and U_j, to the denominator for car driving distance and duration-based access index, respectively. The demand on provider location j is obtained by summing the gravity-discounted influence (sums of inverse distances adjusted for impedance) of all population points within 70 miles. Demand at each provider location was calculated before calculating respective county access scores using the formula (Crooks and Schuurman, 2012). We then calculated the access scores for each county using the demand values obtained for each provider location.

$$V_j = \sum_{j=1}^{H} \left(\frac{Population_c}{drive_{c \to j}} \times \theta_{c \to j} \right)$$

$$U_j = \sum_{j=1}^{H} \left(\frac{Population_c}{duration_{c \to j}} \times \phi_{c \to j} \right)$$

In gravity-based spatial accessibility, we take sums of inverse distance as these inverse distances tend to give more weight or importance to closer objects than farther ones. While in the modified gravity-based model, we sum the inverse distance adjusted with travel impedance and demand.

4 Methods

4.1 Simple regression

We first run a set of simple regressions to capture the correlation between access to care, through substance use treatment, with the existence of Certificate-of-need laws in a given county.

$$Access_c = \alpha + \beta conlaw_c + \gamma border_c + \delta \left(conlaw_c \times border_c \right) + \varepsilon_c \quad (1)$$

where index c represents county. $Access_c$ represents access to substance use treatment facilities. We defined three indicators of access, count, car driving distance, and car driving duration-based access.

$$Access_c \subset (Count\ based\ access_c, Drive\ based\ access_c, Duration\ based\ access_c)$$

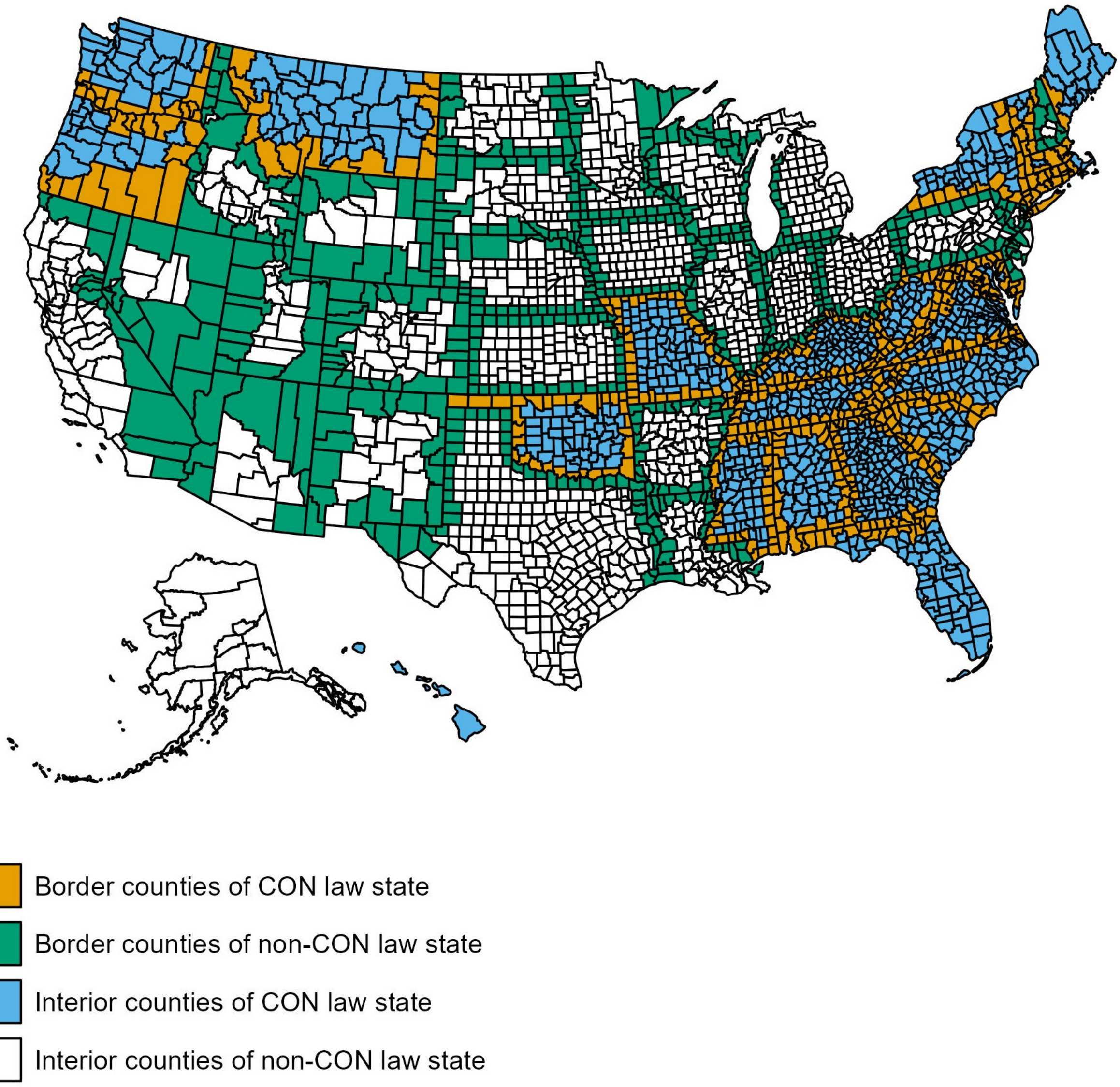
The $conlaw_c$ is a binary indicator variable that takes a value of 1 if counties belong to states with Certificate-of-need laws and 0 otherwise. $border_c$ is a binary indicator which takes a value of 1 if a county of state borders with different states and 0 otherwise. The interaction $(conlaw_c \times border_c)$ is binary indicator which takes a value of 1 if $conlaw_c = 1$ and $border_c = 1$ and 0 otherwise. In simpler terms, the interaction is a binary indicator for counties with Certificate-of-need laws bordering different states.

The coefficient of the regression presented in equation 1 has the following interpretation.

$$\begin{aligned}
\alpha =& E\left[Access_c | conlaw_c = 0, border_c = 0\right] \\
\beta =& E\left[Access_c | conlaw_c = 1, border_c = 0\right] - E\left[Access_c | conlaw_c = 0, border_c = 0\right] \\
\gamma =& E\left[Access_c | conlaw_c = 0, border_c = 1\right] - E\left[Access_c | conlaw_c = 0, border_c = 0\right] \\
\delta =& \{E\left[Access_c | conlaw_c = 1, border_c = 1\right] - E\left[Access_c | conlaw_c = 1, border_c = 0\right]\} \\
& - \{E\left[Access_c | conlaw_c = 0, border_c = 1\right] - E\left[Access_c | conlaw_c = 0, border_c = 0\right]\}
\end{aligned}$$

Consider Figure 2 to examine the regression coefficients of equation 1. The coefficient α represents the intercept in the regression equation, indicating the average level of access to substance use treatment facilities in the interior counties of states without Certificate-of-need laws, represented by the white color in the figure. The β coefficient captures the difference in the average access to substance use treatment facilities between counties with Certificate-of-need laws (blue) and those without (white) while holding constant the effect of bordering other states. Finally, the γ coefficient captures the difference in access to substance use treatment facilities between the counties on the state's border without

Figure 2: substance use Certificate-of-need laws and counties classification



Certificate-of-need laws (green) and the interior counties without Certificate-of-need laws (filled with white color).

The main coefficient of interest is the δ which is the difference between two differences: gold to blue and green to white filled counties' access to substance use treatment facilities. In other words, δ captures the difference between access to substance use treatment facilities among border counties between Certificate-of-need enacting states and border counties without such law after adjusting inherent access within respective states.

5 Results and discussions

5.1 Geographical plot of access measure

Figure 3 shows our three access measures to substance use treatment facilities, with access values displayed as the inverse hyperbolic sine transformation for graphical illustration.

5.2 Descriptive statistics

Table 2 presents descriptive statistics. We include descriptive statistics for access to substance use treatment facilities with level and inverse hyperbolic sine transformation.

Table 2: Descriptive statistics

Variable	**min**	**mean**	**median**	**max**	**sd**	**n**
Access to substance abuse treatment facility						
Level						
Count based	1.00	21.34	10.00	374.00	39.08	2,748
Drive distance based	0.01	0.93	0.35	34.86	2.10	2,666
Drive duration based	0.02	1.23	0.47	50.52	2.80	2,682
Inverse hyperbolic sine						
Count based	0.00	2.59	2.78	6.62	1.52	3,143
Drive distance based	0.00	0.81	0.65	3.63	0.72	3,143
Drive duration based	0.00	0.83	0.71	4.03	0.70	3,143

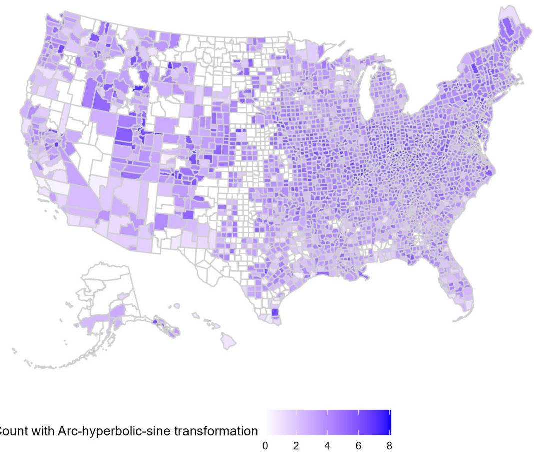
Notes: A higher value of access represents better access to substance use treatment facilities.

5.3 Main results

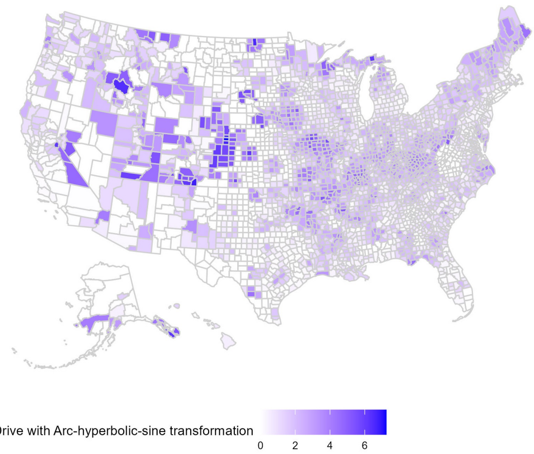
Table 3 presents the results of our regression analysis using the equation presented in equation 1. The dependent variables in columns (1) to (3) are access to substance use treatment facilities measured by count, driving distance, and duration, respectively. Columns (4) to (6) present the results for the Arc-hyperbolic-sine transformed versions of the same variables.

The positive coefficient β indicates that interior counties in states with enacted Certificate-of-need laws have higher access to substance use treatment facilities than those without

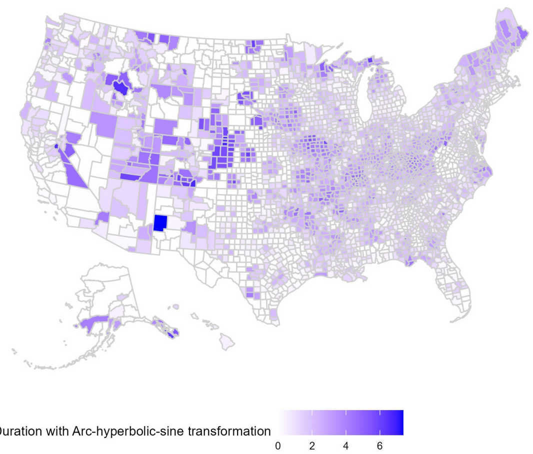
Figure 3: Various index of access to substance use treatment facilities



(a) Count



(b) Drive



(c) Duration

Notes: A higher value of access represents better access to substance use treatment facilities.

Table 3: Mean difference in access to substance use treatment centers

	Dependent variable:					
	Access to substance use treatment centers					
	Level			Arc-hyperbolic-sine		
	Count	Drive	Duration	Count	Drive	Duration
	(1)	(2)	(3)	(4)	(5)	(6)
conlaw : β	0.015	0.235***	0.240***	0.600***	0.160***	0.165***
	(1.441)	(0.082)	(0.080)	(0.055)	(0.032)	(0.031)
border : γ	7.295***	0.454***	0.474***	0.218***	0.201***	0.209***
	(1.566)	(0.089)	(0.087)	(0.060)	(0.035)	(0.034)
conlaw × *border* : δ	5.459**	−0.299**	−0.338***	0.046	−0.082	−0.100*
	(2.331)	(0.132)	(0.129)	(0.089)	(0.052)	(0.051)
Observations	3,141	3,141	3,141	3,141	3,141	3,141
R^2	0.287	0.016	0.016	0.373	0.051	0.051
Adjusted R^2	0.286	0.013	0.014	0.371	0.049	0.049

Notes: Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively. Each model includes a fixed effect based on the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties, and the standard errors are robust to heteroskedasticity.

such regulation. Likewise, the positive coefficient γ suggests that bordering counties have higher access to substance use treatment facilities compared to the interior counties of states without Certificate-of-need regulation. This may be attributed to facilities in states without Certificate-of-need regulations relocating themselves to border counties to attract potential customers from the border counties of states that have enacted Certificate-of-need laws. It is worth noting that both β and γ exhibit inherent differences in access.

The coefficient of primary interest is δ, or the interaction coefficient *conlaw* × *border*, which captures the difference in access to substance use treatment facilities between border counties in states with Certificate-of-need laws and those without such laws after accounting for inherent access differences within each state.

The interaction coefficient *conlaw* × *border* in Table 3, column (1), indicates that border counties in Certificate-of-need enacting states have, on average, 5.459 more substance use treatment facilities than neighboring counties in states without Certificate-of-need laws. However, we should be cautious in interpreting the count variable, as it only represents the number of facilities per 100,000 population and may be biased.

The interaction coefficient $conlaw \times border$ in Table 3, columns (2) and (3), also shows a statistically significant relationship. Specifically, border counties with Certificate-of-need enacting states have, on average, 0.299 fewer substance use treatment facilities per driving mile (after adjusting for driving impedance and facility catchment) and 0.338 fewer facilities per driving minute (after adjusting for driving impedance and facility catchment) than their neighboring counties from states that do not have Certificate-of-need laws.

The coefficient for the interaction term $conlaw \times border$ in columns (5) and (6) of Table 3, which represents the driving distance and duration-based access indicators, respectively, is slightly smaller than in columns (2) and (3). This suggests that the impact of Certificate-of-need laws on access to substance use treatment facilities in border counties is less significant when we adjust for driving distance and duration. Additionally, the statistically insignificant coefficient for the count-based access index could imply that it is a less accurate measure of access to substance use treatment facilities when compared to driving distance and duration-based indicators.

Table 3, columns (2) and (3) estimates suggest that the Certificate-of-need law might reduce access to substance use treatment facilities. These estimates are less intuitive to compare, and we should remain cautious about these results because Table 2 shows that the access indicator is highly skewed.

One way to deal with the skewed variable is to transform the access indicator. Therefore, we follow Bellemare and Wichman (2020) approach and transform our access to substance use treatment facilities with inverse hyperbolic sine transformation.

$$\widetilde{Access} = arcsinh(Access) = ln(Access + \sqrt{Access^2 + 1})$$

We consider the inverse hyperbolic sine transformation of the access indicator and estimate the results of Table 3 column (4) to (6). This transformation changes our regression to arcsinh–linear specification with dummy independent variables. The estimates for $conlaw \times border$ or δ can be redefined and approximated as the percentage change in access as $exp(\delta) - 1$.

Columns (5) and (6) in Table 3 also show negative estimates for the impact of Certificate-of-need laws on access to substance use treatment facilities based on driving distance and duration, respectively, indicating that Certificate-of-need laws counties have less access to substance use treatment facilities compared to border counties without such laws. We find that the Certificate-of-need law in border counties results in a decrease in access to substance use treatment facilities of approximately 7.9% based on driving distance ($exp(-0.082) - 1 \approx -0.079$) with a p-value of 11.9%, and a decrease of approximately 9.5% based on driving duration ($exp(-0.100) - 1 \approx 0.95$) with a p-value of 5.03%.

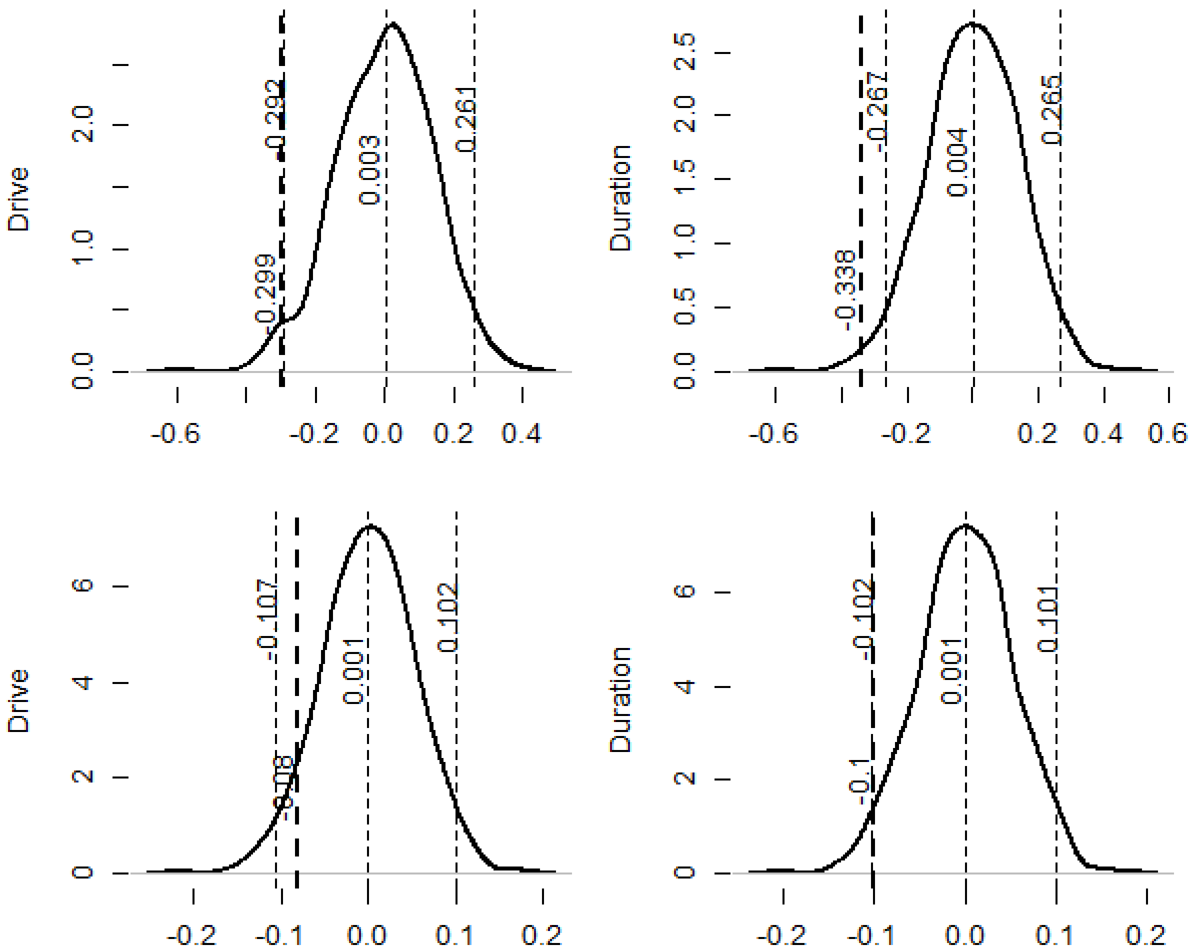
5.4 Robustness

In this section, we stress-test some of our assumptions and deliver several robustness checks for the estimates presented in Table 3.

5.4.1 Randomization inference

Randomization inference tests whether the observed treatment effect is statistically significant; that is, it is unlikely to have occurred by chance. First, we generate the randomization inference effect distribution by randomly permuting the treatment assignments (in our study, the enactment of Certificate-of-need law) 1,000 times and recording the coefficient for the interaction $conlaw \times border$. We then plot the null distribution in Figure 4, with the 95% confidence interval given by the dotted line, along with the bold dotted line representing the observed actual treatment effect from Table 3, columns (2), (3), (5), and (6), respectively.

Figure 4: Randomization inference coefficient



We generate the randomization inference effect distribution by 1,000 times randomly permuting the treatment assignments, in our study, enactment of Certificate-of-need law, and record the coefficient for the interaction *conlaw* × *border*. Each model contains fixed-effect based on the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties. The loosely dotted line shows 2.5% and 97.5% quantiles or lower and upper bound of 95% confidence interval. The dotted line shows the average of the distribution. The bold dotted line shows the estimates from Table 3 column (2), (3), (5), and (6), respectively.

In Figure 4, the randomization inference effect distribution or null distribution visually appears bell-shaped and centers around zero, as expected for a null distribution. The actual treatment effect from Table 3 columns (2), (3), (5), and (6) do not fall within the 95% confidence interval suggesting the actual treatment effect is unlikely to have occurred by chance. It's statistically likely that relaxing the Certificate-of-need law would improve access to care among the border counties.

5.4.2 Multiple regression with covariates

Next, we present Table 4 controlling for other factors that may influence the relationship. We update the regression in equation 1 with the following.

$$Access_c = \alpha + \beta conlaw_c + \gamma border_c + \delta \left(conlaw_c \times border_c\right) + \mathbf{X'}_c \Gamma + \varepsilon_c \tag{2}$$

The $\mathbf{X}_c$ is a matrix that contains k different vectors of observed socioeconomic control variables, Γ is the vector of length k of coefficients associated with the control variables. For our analysis, we control for unemployment, poverty, less-than-high school graduation rates, and median logarithmic transformed income. We gather these county-level data for the year 2020 for the Economic Research Service, US Department Of Agriculture website.[5]

The results presented in Table 4 are comparable to the main results given in Table 3, indicating that Certificate-of-need law reduces access to care among border counties subject to Certificate-of-need laws. In addition, we see statistically significant estimates for the coefficient for the interaction $conlaw \times border$. These results suggest that while relaxing Certificate-of-need laws may improve access to care, other socioeconomic factors such as unemployment, poverty, education, and income also play a significant role.

6 Discussion

We exhibit several results and robustness to indicate that Certificate-of-need reduces access to opioid treatment facilities. In this section, we discuss several aspects of our findings.

Certificate-of-need law mandates that healthcare providers obtain approval from a state board before opening or expanding their services. Therefore Certificate-of-need law reduces supply, limits healthcare competition, and reduces consumers' healthcare options,

[5] https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/

Table 4: Mean difference in access to substance use treatment centers

	Dependent variable:					
	Access to substance use treatment centers					
	Level			Arc-hyperbolic-sine		
	Count	Drive	Duration	Count	Drive	Duration
	(1)	(2)	(3)	(4)	(5)	(6)
conlaw	5.659***	0.328***	0.335***	0.790***	0.207***	0.214***
	(1.448)	(0.086)	(0.083)	(0.057)	(0.034)	(0.033)
border	9.069***	0.450***	0.468***	0.264***	0.200***	0.208***
	(1.497)	(0.088)	(0.086)	(0.059)	(0.035)	(0.034)
conlaw × *border*	3.159	−0.316**	−0.354***	−0.025	−0.091*	−0.109**
	(2.226)	(0.132)	(0.128)	(0.088)	(0.052)	(0.050)
urate	3.395***	0.097***	0.104***	0.129***	0.048***	0.048***
	(0.351)	(0.021)	(0.020)	(0.014)	(0.008)	(0.008)
prate	0.654***	−0.006	−0.010	−0.039***	−0.005	−0.007
	(0.209)	(0.012)	(0.012)	(0.008)	(0.005)	(0.005)
hrate	0.092	−0.043***	−0.048***	0.001	−0.020***	−0.020***
	(0.115)	(0.007)	(0.007)	(0.005)	(0.003)	(0.003)
ln(*income*)	61.368***	−0.364	−0.572**	0.320*	−0.199*	−0.250**
	(4.703)	(0.278)	(0.271)	(0.186)	(0.110)	(0.106)
Observations	3,140	3,140	3,140	3,140	3,140	3,140
R^2	0.355	0.034	0.039	0.398	0.076	0.079
Adjusted R^2	0.352	0.030	0.035	0.396	0.072	0.075

Notes: Significance levels are indicated by ***, **, and * for 1%, 5%, and 10%, respectively. Each model includes a fixed effect based on the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties, and the standard errors are robust to heteroskedasticity.

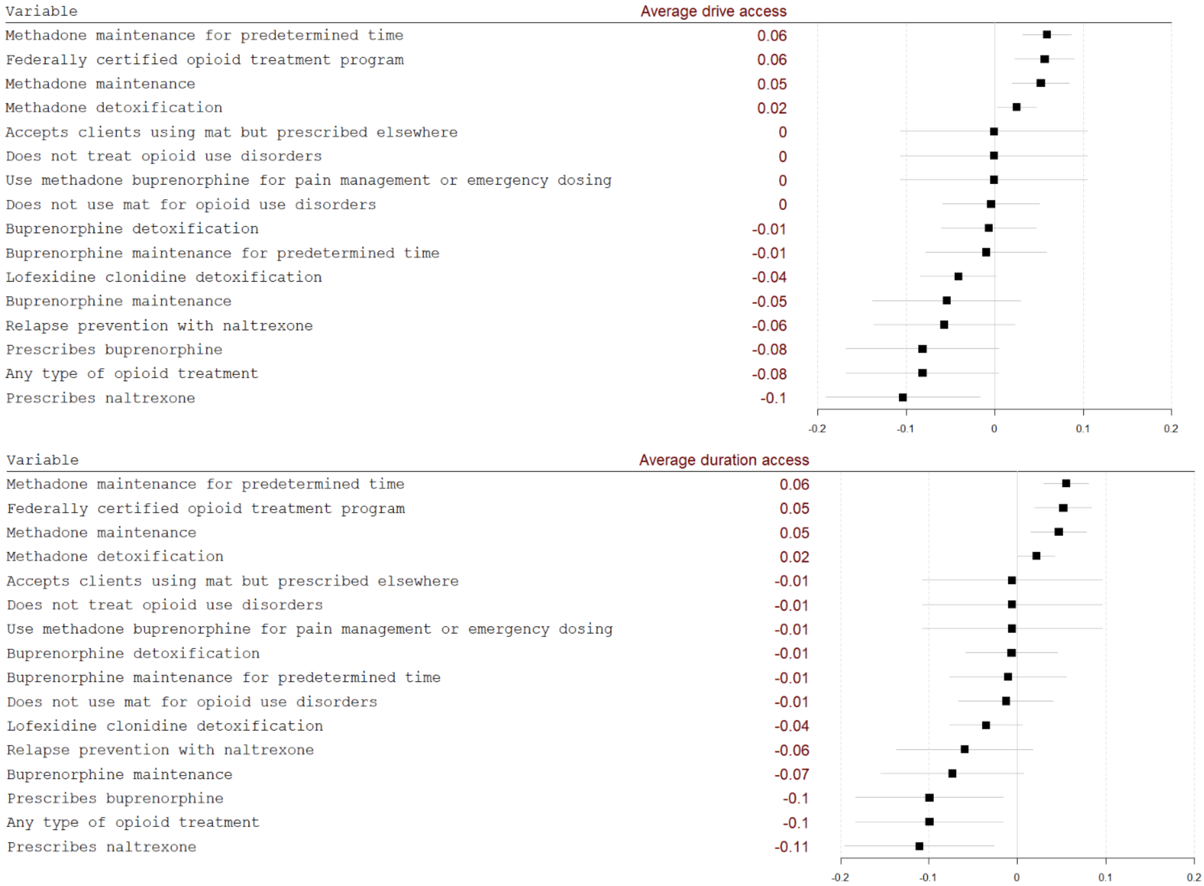
especially in rural or underserved areas where providers may be scarce (Mitchell, 2021), which lowers competition and demand, resulting in less incentive for providers to innovate or improve care. In addition, border counties are often sparsely populated, rural, low-income, and underserved, so healthcare services and facilities may be less profitable (RHIhub, 2022). Therefore, Certificate-of-need laws may give border county providers an advantage over newcomers. Furthermore, existing providers can challenge or oppose new entrants offering similar or competing services or facilities, giving them more market power and influence over the state board (Chiu, 2021). These factors suggest that Certificate-of-need laws may reduce healthcare services and facilities in border counties, particularly those facing access barriers such as distance, transportation, language, culture, and insurance status (NCLS, 2021).

Next, we examine heterogeneity in the negative treatment effect. Our study includes 12,018 unique opioid-related treatment facilities that offer the various services listed in Table 1. First, we examine how Certificate-of-need laws improve or reduce access to these services, as measured by hyperbolic sine transform driving and duration-based access. Next, we estimate the regression model in Equation 1, controlling for the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties as a fixed effect. We then use a forest plot, shown in Figure 5, to plot the coefficient for each service's interaction $conlaw \times border$. The mean estimates for each service are shown in solid boxes with whiskers indicating a 90% confidence interval.

We especially intend to determine to what extent we can falsify our claim that Certificate-of-need could reduce access to opioid treatment facilities. Our study comprises 12,018 unique opioid-related treatment facilities that provide various services listed in Table 1. Therefore, we investigate how much the Certificate-of-need improves or reduces hyperbolic sine transform driving and duration-based access to these services. First, we estimate regression given in equation 1 including the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties fixed-effect. Then, we plot the coefficient for the interaction $conlaw \times border$ for each service with forest plot in Figure 5. Each service in the variable column comprises mean estimates, shown in the solid box and whisker with a 90% confidence interval.

Figure 5 shows that border counties with Certificate-of-need laws have 6-11% lower access for driving and duration for naltrexone and buprenorphine-related services. On the other hand, border counties with Certificate-of-need laws have 2-6% higher driving and duration-based access for methadone-related services and 6% more federally certified opioid treatment programs.

Figure 5: Forest plot



Notes: We only exhibit the coefficient for the interaction $conlaw \times border$. Each model contains fixed-effect based on the National Center for Health Statistics 2013 Urban-Rural Classification Scheme for Counties. Each service in the variable column comprises mean estimates, given in the solid box and whisker with a 90% confidence interval.

The regulation of Opioid treatment programs (OTPs) falls under the purview of the Substance Abuse and Mental Health Services Administration (SAMHSA), which requires OTPs to follow specific guidelines to be certified. The federal regulations for OTPs specify minimum standards for patient care, which may make it more difficult for new providers to enter the market. This could lead to existing OTPs having more market power and potentially expanding their services, increasing federally certified OTPs in states with Certificate-of-need laws. However, this may also limit the availability of other treatment options for OUD, such as office-based physicians who prescribe buprenorphine.

Opioid treatment programs (OTPs) are healthcare facilities that can offer patients medication for substance abuse disorder (OUD), such as methadone, buprenorphine, and naltrexone. To operate, OTPs must comply with federal regulations under 42 CFR 8, which SAMHSA oversees. This oversight may explain why states with Certificate-of-need laws have more federally certified OTPs compared to those without such laws.[6] Furthermore, Certificate-of-need laws may hinder non-OTP providers, like office-based physicians who prescribe buprenorphine, from entering the market. This may cause an increase in demand for OTP services and encourage more OTPs to pursue certification, as explained by Conover and Bailey (2020).

FDA-approved treatments for OUD include methadone and buprenorphine, but regulations for their prescription and dispensing vary. Only DEA, SAMHSA, and state-certified OTPs can dispense methadone. OTPs must follow federal and state methadone treatment regulations for patient admission, dosing limits, counseling services, take-home doses, etc. Practitioners with Schedule III DEA registration can prescribe buprenorphine. Office-based buprenorphine prescriptions do not require OTP certification or an "X" waiver. Some states may restrict buprenorphine prescribing. Methadone-related services may be more affected by Certificate-of-need laws than buprenorphine-related services because of the requirement for OTP certification. Certificate-of-need laws may hinder new OTPs' entry or expansion. Since office-based buprenorphine services don't require OTP certification, Certificate-of-need laws may not apply.

While Certificate-of-need laws may increase access to federally certified opioid treatment programs and methadone-related services, they may also have the unintended consequence of limiting access to buprenorphine-related services by preventing non-OTP providers, such as office-based physicians, from prescribing the medication.

Reforms to Certificate-of-need laws may include full repeal, partial repeal, phased repeal, contingent repeal, administrative relief, and criteria modification (Mitchell, 2021). For example, a full repeal of the substance abuse Certificate-of-need law would mean that a state would no longer require a Certificate-of-need for establishing or expanding substance use treatment facilities or services (NCLS, 2021). Florida and West Virginia are on

[6] https://www.law.cornell.edu/cfr/text/42/8.11

the path to partial repeal, while several states repealed in stages with automatic sunsets. For example, Arkansas and Colorado reform their Certificate-of-need laws contingent on neighboring states' actions.

7 Conclusion

Healthcare accessibility is a significant indicator of favorable health outcomes. This paper adds to that discussion of the impact of supply-side barriers to access. For example, in states with Certificate-of-need laws, a supply-side barrier to competition, there is evidence of reduced access to substance use treatment facilities. This negative relationship is concerning from a policy standpoint. These policies aim to reduce healthcare costs to prevent unnecessary spending on services when there is a lack of documented need. However, these policies' unintended consequences are associated with reduced access to needed services.

We also add to the discussion the importance of substance use treatment accessibility. States with Certificate-of-need laws for substance use treatment showed reduced access to treatment facilities. When considering how individuals access and utilize these services, it is crucial to recognize the importance of geographic distance in the ability of people who use drugs to obtain and maintain treatment. This is particularly important for certain types of treatment, such as outpatient care and medication-assisted treatment (such as methadone, buprenorphine, and naltrexone treatments), where traveling to and from treatment sites is essential for successful treatment outcomes. Moreover, individuals who use drugs often encounter additional obstacles, such as financial and transportation challenges, that further restrict their access to treatment.

States with current Certificate-of-need laws should assess whether their policies achieve the intended outcomes. The literature is firmly against this. Our findings contribute to this discussion by providing evidence that Certificate-of-need laws for substance use treatment facilities reduce accessibility to these vital services. Further research is needed to understand the specific impact of these laws on treatment admission and success, as well as the broader implications for health outcomes related to drug use, such as overdose and infection rates. Such research can inform policymakers whether these laws achieve their goals and whether alternative policies should be considered.

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