

Prevention of 90-day Detox Readmission for Opioid use Disorder by A Community-Based Life-Changing Individualized Medically Assisted Evidence-based Treatment (C.L.I.M.B.) Program: A Quasi-Experimental Design

Zhehui Luo (✉ zluo@msu.edu)

Michigan State University

Canopy Roychoudhury

Blue Cross and Blue Shield of Michigan

William S. Pompos

Blue Cross and Blue Shield of Michigan

James DiMaria

Blue Cross and Blue Shield of Michigan

Cynthia Robinette

Blue Cross and Blue Shield of Michigan

Purva Gore

Blue Cross and Blue Shield of Michigan

Rohon Roychoudhury

Michigan State University

William Beecroft

Blue Cross and Blue Shield of Michigan

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Abstract

Background: Evidence for community-based detox readmission prevention strategies for opioid use disorder (OUD) is scant. We evaluated a pilot program designed to provide individualized and structured treatment plan, including addressing prolonged withdrawal symptoms, family/systems assessment, contingency management, and medically assisted treatment.

Methods: A non-randomized quasi-experimental design was used to compare the pilot sites (treatment) and comparison sites before and after the program started, i.e., a simple difference-in-differences (DID) strategy. Adults 18 years and older who meet the Diagnostic and Statistical Manual of Mental Disorders version 5 criteria for OUD and had a detox admission at any OUD treatment facility in two study periods between 5/2018 and 12/2019 are included. Readmission for detox in 90-days after the initial detox was the primary outcome. Multiple statistical estimation methods were used to adjust for potential confounding factors between treatment and comparison groups.

Results: A total of 2,320 unique patients with 2,443 initial detox admissions in the pre- and post-periods were compared. Compared with the comparison patients, the C.L.I.M.B. patients had higher readmission in the pre-period (unadjusted readmission rates 16.4% vs. 10.0%), but similar rates in the post-period (11.8% vs. 10.1%) after the implementation of the pilot program. For the primary outcome 90-day readmission, all DID estimates were not statistically significant (adjusted estimates ranged from 6.0 to 17.3 percentage points difference favoring the C.L.I.M.B. program). For the secondary outcomes of service utilization, the C.L.I.M.B. program had reduced the proportion of patients using the intensive outpatient treatment compared to the comparison group and the statistically significant DID estimates ranged from 13 to 18 percentage point differences for the intensive outpatient treatment.

Conclusions: Treating OUD as a chronic condition instead of an acute episodic condition for patients in the community is feasible and has a potential to reduce intensive outpatient services. Although the small sample size of the pilot program precluded us to draw a definitive conclusion, we believe more OUD treatment facilities should work with health plans to standardize care for patients with OUD and promote lowering readmission for inpatient withdrawal management.

Introduction

Almost 500,000 Americans died from an opioid-related overdose between 1999 and 2019 and the age-adjusted synthetic opioid-involved death rate increased 15% from 9.9 to 11.4 per 100,000 population.¹ The use of inpatient addiction treatment, though lacks efficacy support,² increased from 38% in 2004-2008 to 52% in 2009-2013 among individuals who received treatment for opioid use disorder (OUD) in the prior 12 months,³ and the rates of opioid-related detoxification discharge decreased from 31.5 to 27.4 per 100,000 persons between 1993 and 2016.⁴ Evidence-based strategies – including reducing opioid prescribing and increasing access to treatment of OUD – must be adapted and deployed together to address the crisis and save lives.⁵ In the past few decades, OUD has been treated on an episodic basis with poor outcomes and high relapse rates. Many patients and providers lament the mismanagement of OUD, especially the lack of “ownership” in handling the tapering process.^{6,7} Methadone, buprenorphine and naltrexone have been shown to prevent relapse in clinical trials,^{8,9} however in 2016 only 36% of substance use treatment facilities with outpatient services offered any medication treatment (buprenorphine 25%, naltrexone 21%, methadone 10%)¹⁰ and in California only 11% of all detoxification episodes were followed by maintenance treatment within 14 days in 2012.¹¹ Not all treatment facilities can meet the special needs by patients with histories of unemployment, homelessness, and psychiatric comorbidities that require social service interventions not usually found in the medical system.^{12,13} The American Society of Addiction Medicine (ASAM) recommends the OUD treatment choice be based on a shared decision making process.^{14,15} Strategies specifically designed for relapse prevention and withdrawal management are equally important for this chronic relapsing disease.¹⁶

Grounded in the community-based chronic care model, a pilot program (Community-based Life-changing Individualized Medically assisted evidence-Based treatment, [C.L.I.M.B.]) was implemented on May 1 and Dec 1, 2018, by the Blue Care Network (BCN) and Blue Cross Blue Shield (BCBS) of Michigan respectively, for individuals 18 years and older who met the

Diagnostic and Statistical Manual of Mental Disorders version 5 criteria for OUD and were admitted to inpatient detox at two sites. This paper evaluates the impact of the program on detox admission prevention in 90 days after discharge from inpatient facilities. The question is: If the C.L.I.M.B. program is rolled out to sites like the pilot sites will it reduce 90-day readmission among OUD patients?

Methods

Design

Consistent with the quasi-experimental two-group pre-post design, we used the difference-in-differences (DID) method to ameliorate potential confounding bias.^{17,18} The underlying assumption of the DID method is that the change in readmission rates from pre- to post-period in the comparison group is a good proxy of the counterfactual change in the pilot group had there been no pilot program (Figure S1 in supplemental materials). The effect of interest is the average treatment effect on the treated which answers the question: for patients treated in the pilot sites, was the program a cause for the change in readmission rate? On the probability scale, a DID method estimates the difference of risk differences (DRD); and on the odds ratio (OR) scale, a DID method estimates the ratio of ORs (ROR). The pre-and post-periods for the BCN (a health maintenance organization [HMO]) patients were 7/1/2016 to 4/30/2018 and 5/1/2018 to 8/31/2019; the corresponding periods for the BCBSM (a preferred provider organization [PPO]) patients were 2/1/2017 to 11/30/2018 and 12/1/2018 to 3/30/2020. In the post-period, another site (Brighton Center) implemented a program like C.L.I.M.B.; thus, to avoid contamination, patients whose initial detox occurred at that site in the post-period were excluded (Figure 1). The pilot program was approved by the BCN and BCBSM medical directors, and the current evaluation was approved by the Institutional Review Board of Michigan State University as non-human subject research (STUDY00000846).

(Figure 1 Here)

Patients

Patients 18 years or older, who had a detox inpatient stay for a diagnosis of OUD in any of the two pre-periods were included in the study. To ensure data completeness, a patient had to be enrolled in the health plan for 6 or more months before the initial detox in the pre-period to capture baseline comorbidity; and the initial detox did not occur within 90-days of each period's end date.

Intervention

Following ASAM guidelines,^{14,15} the C.L.I.M.B. program (Figure S1) included services for the continuum of OUD cycle, including detoxification, residential services, partial hospitalization/intensive outpatient services, outpatient services with medically assisted treatment (MAT), and a modified smartphone support application (app), called A-CHESS, originated in 2011 at the University of Wisconsin Center for Health Enablement Support System (CHESS), which is a comprehensive relapse prevention tool based on the self-determination theory¹⁹ to help patients with substance use disorders (SUDs) succeed in recovery.

Prior to the pilot program implementation, providers in the two sites provided same services as other OUD treatment facilities. During the implementation, they agreed to follow the C.L.I.M.B. codified protocol (detailed in Appendix A) with an emphasis on the master-treatment-plan development, family/system assessment, warm handoff, completion of tasks regardless of length of stay, and the use of A-CHESS. Key features of A-CHESS²⁰ included :1) a "Help" button linked to the patient's preapproved supporters, 2) positive and potentially distracting games, and audio-video relaxation recording; 3) cognitive behavioral therapy boosters; 4) functionality monitoring with self-assessment tools; 5) a global positioning system location tracker that will

initiate a patient-defined action (e.g., contacting sober coach) when s/he approaches a high-risk location, and 6) just-in-time feedback via a counselor dashboard.

Comparison Group

All other OUD treatment facilities in the U.S. that BCBSM and BCN members attended for inpatient detox in the study period constituted the comparison group. The usual care available at each facility varied and was expected to be representative of current practice in the field. Not all facilities covered the continua of LOCs.

Main Measures

Primary outcome: 90-day detox readmission after an initial detox inpatient stay at any facility. Readmission was identified by the same method as the initial detox: any inpatient stay with a diagnosis of F11.x or F11.xx using the International Classification of Diseases, 10th version, Clinical Modification (ICD-10-CM) codes, and revenue codes 01x6 (x=1, 2,3,4, or 5).

Secondary outcomes: Other ASAM LOCs, including partial hospitalization/intensive outpatient services, outpatient services and MATs. MATs were identified using National Drug Codes in pharmacy claims and the Current Procedural Terminology codes; and revenue codes and/or procedure codes were used to find LOC 1.0-2.5 (partial hospitalization/intensive outpatient services/outpatient) services (list of these codes available upon request).

Treatment groups: the National Provider Identifier codes for the two pilot facilities were used to identify patients in the pilot group. Patients in the other treatment facilities were the comparison.

Comorbidity: the Agency for Healthcare Research and Quality Clinical Classification Software Refined version (v2021.2)²¹ based on the ICD-10-CM codes was used to find in medical claims of comorbid conditions in the 6 months prior to the initial detox in each period, including mood disorders; anxiety-, fear-, trauma- or stressor-related disorders; alcohol-, cannabis-, sedative-, stimulant- hallucinogen- or inhalant- related disorders; neoplasms; suicidal ideation/attempt or intentional self-harm; endocrine, nutritional and metabolic diseases; diseases of the nervous, circulatory, respiratory, digestive, musculoskeletal system, or genitourinary systems. Emergency room visits in the 6 months prior to the initial detox in each period were identified using revenue codes 045x (x=0-9).

Covariates: Patient's age, sex, HMO or PPO plan types, and residential zip codes were extracted from health plan enrollment files. The 5-digit zip codes were linked to the census tracts using the U.S. Department of Housing and Urban Development zip code crosswalk files²² where a census tract with the highest residential ratio was chosen when multiple tracts were within the same zip code.²³ Past research found that living in a disadvantaged neighborhood was associated with worse health conditions and increased healthcare utilizations. We used the 2018 Area Deprivation Index (ADI),^{24,25} 2015 Childhood Opportunity Index (COI),²⁶ and 2018 Social Vulnerability Index (SVI)²⁷ to approximate the neighborhood characteristics and as proxies to patient socioeconomic status. Higher ADI rankings and SVI scores indicate more disadvantaged neighborhoods; but higher COI scores indicate more opportunities. All indices were transformed to have a range from 0 to 100.

Analytic Approach

We compared the differences in covariates and comorbidities between the C.L.I.M.B. and comparison group in the pre- and post-periods using chi-square tests for categorical variables and t-tests for continuous variables. As in the tradition for propensity score analysis, we also presented the standardized differences (difference divided by the pooled standard deviation) between the two group. When the absolute value of the standardized difference is greater than 0.1, it is indicative of non-negligible difference.²⁸ We estimated the DID effects using six statistical methods to triangulate evidence: 1) multivariable logistic regression adjustment (RA) controlling for comorbidities and covariates; 2) augmented inverse

probability weighted (IPW) estimation²⁹ where covariates for the outcome and the propensity scores (PS) models were selected using logistic lasso;³⁰ 3) IPW estimation where the PS was estimated using logistic regressions controlling for the same covariates in the RA model; 4) IPW-RA double robust method;³¹ 5) bias-corrected single nearest neighbor matching method³²; and 6) PS matching with a caliper 0.2. The 95% confidence intervals (CI) were estimated using the percentile-based bootstrap CI with 1,000 bootstrapped samples. All analyses were performed in Stata version 17.³³

Sensitivity Analyses

We performed two sets of sensitivity analysis. First, we excluded 123 patients (236 admissions) who were in both pre- and post-periods, because the analyses may be contaminated by the correlations between observations for the same patients, especially when the patient was in different treatment groups across periods. Secondly, many randomized controlled trials (RCTs) include stringent inclusion/exclusion criteria. We applied some of the patient-selection criteria of the MAT + A-CHESS trial²⁰ that can be defined using our data to assess the robustness of the main-analysis estimates in a selected sub-population who had no acute medical problems with immediate inpatient treatment needs, no history of psychotic disorders, and not pregnant.

Results

A total of 2,320 unique patients with 2,443 detox admissions in the pre- and post-periods were included in the main analyses. Table 1 shows that in the pre-period, C.L.I.M.B. patients were more likely to be in the HMO plans, had more mood disorders, and diseases of the musculoskeletal system than patients in comparison sites; however, in the post-period, C.L.I.M.B. patients had fewer other substance-related disorders, or diseases of the nervous or digestive systems than patients in the control sites, mainly due to increased prevalence of these condition in the control group. The largest and most significant differences between the groups were at the neighborhood level. C.L.I.M.B. patients were more likely to live in one the 100 largest metropolitan areas, had lower ADI, higher COI, and lower SVI scores, i.e., they were from relatively more well-to-do neighborhoods.

Before using the PS for adjustments, the raw standardized differences (Table 2) showed consistent patterns as in Table 1. After weighting, the standardized differences were reduced to less than 0.1 for all except for 4 variables (mood disorder, disease of the musculoskeletal system and connective tissue, living in one of the 100 largest metropolitan areas, and mean SVI minority/language score, Table 2 column 2) in the pre-period; however, weighting did not improve balance in the post-period (17 variables had standardized difference greater than 0.1, Table 2 column 4). The residual imbalance was adjusted using these 4 and 17 variables in the nearest neighbor matching method. The few variables selected by the logistic lasso generated a bi-modal PS distribution (Figure 2) but there was good overlap between the PS of C.L.I.M.B. and comparison groups.

(Figure 2 Here)

All six methods (Table 3) gave similar estimated DRDs and RORs between groups over time. Before the pilot implementation, C.L.I.M.B. patients had statistically significantly higher 90-day readmission rates than comparison patients (16.4% vs. 9.3 to 11.6% estimated by various adjustment methods); however, after the pilot implementation, readmission rates decreased significantly in the C.L.I.M.B. group to 11.8% whereas the adjusted rates in controls did not change significantly (varying from 11.1% to 23.1%). The DRDs and RORs were not statistically significant (adjusted DRDs ranged from 6.0 to 17.3 percentage points favoring the pilot group). Compared with that in the pre-period, patient profiles changed a little in both groups, although the changes were not statistically significant in the C.L.I.M.B. group due to small sample size (Table S1 in supplemental materials). The two sensitivity analyses (N=2,197 observations in Table S2 and N=2,121 observations in Tables S3) led to results qualitatively the same as the main analyses.

For the secondary outcomes of service utilization, we found the C.L.I.M.B. program had reduced the proportion of patients using the intensive outpatient treatment compared to the comparison group (Table 4), but the proportions of MAT and outpatient treatments remained stable. The DID analysis using the same methods above showed statistically significant DRDs ranging from 13 to 18 percentage point differences for the intensive outpatient treatment (Table 5).

Discussion

The ASAM criteria advocate for individualized, assessment-driven treatment and the flexible use of services across a broad range of care, which can be offered by single or multiple providers with “(1) seamless transfer between levels of care, (2) philosophical congruence among the various providers of care; and (3) timely arrival of the patient’s clinical record at the next provider.”³⁴ The C.L.I.M.B. program was designed using these principles. Although there was a significant decrease in 90-day readmission rates in the C.L.I.M.B. group from 16 to 11% from the pre- to post-period, the DID estimates compared with a community control group were not statistically significant. The program did reduce intensive outpatient treatment compared to the control group, which reflected the guiding principle for continued management of withdrawal in a lower LOC.

There is limited literature on the impact of a community-based OUD chronic care model on reducing detox readmission after the initial detox discharge. In a commercially insured population in the U.S., those entering initial care in an inpatient setting with only short-term inpatient stay without medication for opioid use disorder (MOUD) had a 4% overdose rate and 74% all-cause rehospitalization in one year; and from 2011 to 2017 there was a significant decrease in overdose rate but no change in all-cause rehospitalization.³⁵ A small retrospective study in an urban academic hospital found that in-hospital initiation of opioid agonist treatment (OAT) through a hospital-based SUD consultation-liaison team did not reduce 180-day all-cause rehospitalization compared with usual care.³⁶ However, a large RCT among eligible medical/surgical patients in the same setting with a more comprehensive patient-navigation service led to lower incidence of all-cause readmissions in 30-, 90-, 180- and 365-days, but no significant difference in positive urine drug test.³⁷ The above studies suggest treating OUD on an episodic basis without integration in all levels of care is unlikely to reduce readmission related to detox.

Several reasons may explain our largely null findings. First, the pilot program aimed to recruit 300 patients in the program, however, fewer than 200 patients enrolled. Although the program continues in operation, current evaluation was limited to the 16-month period after the program initiation. The lack of power was the main reason why the DID effects were not statistically significant.

Second, one of the key components of the pilot program was the integration of the smartphone app A-CHESS to the clinical practices. Unfortunately, few patients used A-CHESS after they signed up on the phone at discharge (confirmed by the A-CHESS data) and providers’ feedback suggested that other apps existed with features that patients preferred. In December 2018, the Food and Drug Administration cleared the first smartphone app, reSET-O, to be used alongside the MAT to help improve retention in an outpatient setting. A group of Yale experts also developed a free app, BUP Home Induction, as a companion to MAT. Compared with these tools, the A-CHESS suffers from a few shortcomings. It is not free, and it does not provide the feedbacks that are salient to the patients, e.g., the money saved due to abstinence. Like many apps, systematic evaluation of the efficacy of A-CHESS for OUD is needed.³⁸

Third, the pilot program was implemented in the height of the opioid epidemic when many SUD facilities were undergoing changes in practice. While the pilot sites had all ASAM LOC services, the control sites may vary cross-sectionally and over time. The National Survey of Substance Abuse Treatment Services (NSSAT) data showed that the proportion of SUD facilities in the U.S. that offer MOUD increased from 10% in 2007 to 36% in 2016.¹⁰ In a secret shopper audit study in 2019 Beetham et al. found 29% of residential treatment programs offer OAT.³⁹ Using the 2016 and 2019 NSSAT data, we found that the percent of facilities that offered a broad range of services, including partial hospitalization/intensive outpatient services, outpatient detoxification, outpatient methadone/buprenorphine maintenance, and maintenance with medically supervised withdrawal had increased from 15% in 2016 to 21% in 2019. Hence, the control sites may be experiencing improvements in services in the study period. Because we did not have the linkage to control facilities in our analyses, we had no good description on the type

of services they provided. Through our connection with the providers in one large facility (Brighton Center), we knew they initiated a similar program like the C.L.I.M.B. in the same period, and for that reason we excluded it from our post-pilot period.

There are some strengths of our study. Although RCTs are deemed the gold standard to establish evidence of efficacy of a treatment, practitioners tend to find many trial-tested treatments less effective in the real world. Community-based programs do not have strict inclusion/exclusion criteria as RCTs and using quasi-experimental design such as the DID method in our analysis is a potentially valid approach to evaluate real world interventions, provided that the assumptions for the DID methods are carefully considered and deemed plausible. We consider our careful analyses and interpretation of the results as a strength.

Second, we used multiple statistical estimators to quantify the causal effect of interest and the estimates were largely consistent with each other, which was reassuring. Using administrative claims data for research, we frequently find ourselves dealing with many covariates and multiple regression-based analyses tend to mask the differences in patient characteristics between groups. Using clearly defined causal effect of interest, i.e., the average treatment effect on the treated, which answers the specific question: “for patients treated in the pilot sites, was the program a cause for the change in readmission rates?”, we do not lose sight of the goal of the evaluation and do not interpret regression coefficients causally when they do not represent causal effects of interest.

Our study has several limitations. Foremost, our outcome and covariates were all based on administrative healthcare data. Although prevention of readmission was an important goal for the insurers, treatments for detox are not limited to the inpatient setting. Compared with measures of relapse in RCTs (e.g., 4 consecutive weeks of opioid use by urine toxicology or self-report, or 7 consecutive days of self-reported use in Lee et al.⁹), inpatient admissions do not capture all relapses. However, in the real world, health plans rely on these data to identify target population for quality improvement.

Second, a key untestable assumption for the DID methods is the parallel trend assumption (Figure S2), i.e., the change in 90-day readmissions from pre- to post-periods in the control group is a good proxy for the counterfactual change in pilot group had there been no pilot intervention. In our data, the readmission rates in the control group over the pre- to post-pilot periods virtually unchanged. However, in the U.S. population from 2008 to 2016 there was significant decline in the rate of opioid-related discharges with detoxification services during the hospitalization,⁴ which, although not a direct measure of readmission, presumably was indicative of decline in readmission for detoxification as well. As the treatment modality shifts toward MOUD delivered in an outpatient setting, it is possible that the control group did not reflect the counterfactual change that the pilot group would have experienced. Thus, our DID estimates may be an overestimate of the true effect.

Finally, many patients came to the pilot sites from afar and after leaving the facilities they may not complete the full spectrum of care in the pilot program or benefit from all the services offered. However, since the proportions of patients receiving MAT or outpatient treatment in the pilot sites remained virtually unchanged, we believe the reduction in the intensive outpatient treatment in the pilot group was not due to missing data. As OUD is a chronic disease, patient’s willingness to follow the treatment plans is critical for recovery. Finding factors that improve treatment adherence and retention is an important next step in the design for effective intervention in the future.

Conclusions

Our study used a carefully conceived quasi-experimental design to evaluate a community-based treatment of OUD. The pilot program demonstrated that implementing a chronic care model for OUD in the community was feasible.⁴⁰ Although the small sample size precluded us from drawing a definitive conclusion regarding inpatient detox readmission, we believe more OUD treatment facilities should work with health plans to standardize care for patients with OUD and promote lowering readmission for inpatient withdrawal management.

Abbreviations

C.L.I.M.B.: community-based life-changing individualized medically assisted evidence-based treatment

OD: opioid use disorder

DID: difference-in-differences

ASAM: American Society of Addiction Medicine

BCN: Blue Care Network

BCBS: Blue Cross Blue Shield

DRD: difference of risk differences

OR: odds ratio

ROR: ratio of odds ratios

PPO: preferred provider organization

HMO: health maintenance organization

ADI: area deprivation index

COI: childhood opportunity index

SVI: social vulnerability index

RA: regression adjustment

IPW: inverse probability weighted

PS: propensity scores

CI: confidence interval

RCT: randomized controlled trial

MAT: medically assisted treatment

A-CHESS: Addiction-Center for Health Enablement Support System

LOC: level of care

SUD: substance use disorder

ICD-10-CM: International Classification of Diseases, 10th version, Clinical Modification

Declarations

- **Ethics approval and consent to participate**

The study was approved by the Institutional Review Board of Michigan State University as non-human subject research (STUDY00000846) and no consent to participate was required.

• Consent for publication

All authors approved the final version of the manuscript for submission and publication.

• Availability of data and materials

All data are proprietary and not publicly available.

• Competing interests

None.

• Funding

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• Authors' Contributions

ZL: conceptualization, methodology, writing– original draft preparation, reviewing and editing.

CR: data curation, writing–original draft preparation and editing.

WSP: program implementation, writing–reviewing and editing.

JD: data preparation, writing–reviewing and editing.

CMR: data curation, writing–reviewing and editing.

PHG: data curation, writing–reviewing and editing.

RR: literature summary, writing–reviewing.

WB: program design and implementation, conceptualization, writing–reviewing and editing.

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Tables

Table 1. Demographic characteristics, medical claims six months prior to detox in the pre- and post-period

	Pre-period			Post-period		
	Control	C.L.I.M.B.	p-value ‡	Control	C.L.I.M.B.	p-value ‡
	N=1,385	N=318		N=545	N=195	
Age category	N (%)	N (%)		N (%)	N (%)	
18-<25	407 (29.4)	88 (27.7)	0.636	154 (28.3)	53 (27.2)	0.47
25-<35	364 (26.3)	90 (28.3)		147 (27.0)	45 (23.1)	
35-<45	212 (15.3)	42 (13.2)		95 (17.4)	43 (22.1)	
45+	402 (29.0)	98 (30.8)		149 (27.3)	54 (27.7)	
Female	467 (33.7)	96 (30.2)	0.228	176 (32.3)	69 (35.4)	0.43
HMO	245 (17.7)	154 (48.4)	<0.001	57 (10.5)	87 (44.6)	<0.001
Comorbidity 6 months prior to initial detox						
Had no claims	156 (11.3)	34 (10.7)	0.770	51 (9.4)	17 (8.7)	0.79
had detox	78 (5.6)	18 (5.7)	0.984	48 (8.8)	15 (7.7)	0.63
Had emergency room visits	708 (51.1)	160 (50.3)	0.796	270 (49.5)	89 (45.6)	0.35
Had opioid use disorder diagnosis	677 (48.9)	160 (50.3)	0.645	295 (54.1)	102 (52.3)	0.66
Substance-related disorders *	331 (23.9)	72 (22.6)	0.634	174 (31.9)	44 (22.6)	0.01
Mood disorders †	550 (39.7)	148 (46.5)	0.026	236 (43.3)	84 (43.1)	0.96
Alcohol-related disorders	260 (18.8)	68 (21.4)	0.287	135 (24.8)	36 (18.5)	0.07
Anxiety/fear/trauma/stressor-related disorders	585 (42.2)	145 (45.6)	0.275	257 (47.2)	84 (43.1)	0.33
Suicidal ideation/attempt/intentional self-harm	130 (9.4)	31 (9.7)	0.842	45 (8.3)	12 (6.2)	0.35
Neoplasm	83 (6.0)	18 (5.7)	0.821	32 (5.9)	11 (5.6)	0.91
Endocrine, nutritional, and metabolic diseases	418 (30.2)	100 (31.4)	0.658	182 (33.4)	62 (31.8)	0.68
Diseases of the nervous system	569 (41.1)	120 (37.7)	0.273	229 (42.0)	66 (33.8)	0.05
Diseases of the circulatory system	448 (32.3)	92 (28.9)	0.238	185 (33.9)	57 (29.2)	0.23
Diseases of the respiratory system	381 (27.5)	83 (26.1)	0.611	155 (28.4)	58 (29.7)	0.73

Diseases of the digestive system	350 (25.3)	75 (23.6)	0.531	152 (27.9)	38 (19.5)	0.02
Diseases of the musculoskeletal system and connective tissue	653 (47.1)	130 (40.9)	0.043	238 (43.7)	78 (40.0)	0.37
Diseases of the genitourinary system	280 (20.2)	62 (19.5)	0.773	118 (21.7)	36 (18.5)	0.35
Injury, poisoning and certain other consequences of external causes	455 (32.9)	119 (37.4)	0.120	177 (32.5)	58 (29.7)	0.48
Live in one of the 100 largest metro areas	965 (69.7)	270 (84.9)	<0.001	377 (69.2)	169 (86.7)	<0.001
Neighborhood characteristics	Mean (SD)	Mean (SD)		Mean (SD)	Mean (SD)	
Mean ADI state rank	48.4 (21.6)	44.8 (23.9)	0.009	51.3 (22.3)	44.0 (24.4)	<0.001
Mean ADI national rank	59.8 (19.4)	57.1 (22.1)	0.033	61.1 (20.3)	55.6 (23.4)	<0.01
Mean childhood opportunity index	54.1 (20.8)	56.0 (23.4)	0.149	51.7 (21.6)	57.8 (24.2)	<0.01
Mean SVI socioeconomic score	44.9 (20.2)	42.0 (22.4)	0.022	47.0 (20.5)	39.5 (22.9)	<0.001
Mean SVI household/disability score	52.8 (18.2)	48.0 (18.7)	<0.001	54.1 (17.7)	46.0 (19.5)	<0.001
Mean SVI minority/language score	31.8 (17.7)	35.3 (16.8)	0.001	35.0 (19.0)	35.6 (17.3)	0.66
Mean SVI housing/transportation score	39.9 (14.6)	36.0 (14.7)	<0.001	42.3 (15.9)	34.1 (14.0)	<0.001

*. Including cannabis-, sedative-, stimulant- hallucinogen- or inhalant-related substances

†. Including depressive disorders, bipolar disorders, and other specified mood disorders

‡. p-values are based on chi-square tests for categorical variables and t-tests for continuous variables

C.L.I.M.B. = Community-based Life-changing Individualized Medically assisted evidence-Based treatment

ADI = area deprivation index

SVI = social vulnerability index

SD = standard deviation

Table 2. Standardized difference (SD) between C.L.I.M.B. and comparison in the pre- and post-period respectively

	Pre-period		Post-period	
	Raw SD	Weighted SD	Raw SD	Weighted SD
Age category				
18-<25	0.038	-0.078	0.024	0.019
25-<35	-0.046	0.025	0.089	-0.198
35-<45	0.059	-0.047	-0.119	0.105
45+	-0.039	0.090	-0.008	0.086
Female	0.075	-0.099	-0.066	0.168
HMO	-0.757	-0.040	-0.933	-0.060
Comorbidity 6 months prior to initial detox				
Had no claims	0.018	0.021	0.022	-0.083
had detox	-0.001	-0.030	0.040	-0.046
Had emergency room visits	0.016	-0.038	0.078	-0.070
Had opioid use disorder diagnosis	-0.029	0.025	0.037	-0.120
Substance-related disorders *	0.030	-0.051	0.206	-0.161
Mood disorders †	-0.139	0.143	0.005	-0.017
Alcohol-related disorders	-0.066	0.028	0.150	-0.129
Anxiety/fear/trauma/stressor-related disorders	-0.068	0.032	0.082	-0.078
Suicidal ideation/attempt/intentional self-harm	-0.012	-0.018	0.079	-0.187
Neoplasm	0.014	0.002	0.010	0.005
Endocrine, nutritional, and metabolic diseases	-0.028	0.062	0.034	-0.055
Diseases of the nervous system	0.068	-0.041	0.167	-0.223
Diseases of the circulatory system	0.073	-0.039	0.101	-0.135
Diseases of the respiratory system	0.032	-0.061	-0.029	-0.007
Diseases of the digestive system	0.039	-0.037	0.193	-0.192
Diseases of the musculoskeletal system and connective tissue	0.126	-0.103	0.074	-0.094
Diseases of the genitourinary system	0.018	-0.015	0.079	-0.026
Injury, poisoning and certain other consequences of external causes	-0.097	0.081	0.059	-0.063
Live in one of the 100 largest metro areas	-0.344	0.302	-0.404	0.274
Neighborhood characteristics				
Mean ADI state rank ‡	0.163	0.022	0.317	-0.130
Mean ADI national rank	0.132	0.029	0.261	-0.138
Mean childhood opportunity index	-0.090	-0.078	-0.274	0.093
Mean SVI socioeconomic score §	0.142	0.058	0.355	-0.143

Mean SVI household/disability score	0.265	0.019	0.443	-0.258
Mean SVI minority/language score	-0.202	0.168	-0.037	0.123
Mean SVI housing/transportation score	0.267	-0.068	0.529	-0.136

*. Including cannabis-, sedative-, stimulant- hallucinogen- or inhalant-related substances

†. Including depressive disorders, bipolar disorders, and other specified mood disorders

C.L.I.M.B. = Community-based Life-changing Individualized Medically assisted evidence-Based treatment

SD = standardized difference, comparison group minus treatment group divided by the pooled standard error

ADI: area deprivation index

SVI: social vulnerability index

Table 3. Readmission rate in pre- and post-period and C.L.I.M.B. and comparison groups

	Pre-period				Post-period				Treatment Effect			
	C.L.I.M.B.	Control	RD	OR	C.L.I.M.B.	Control	RD	OR	DRD	95% CI*	ROR	95% CI*
ATET Unadjusted	16.4	10.0	6.3	1.75	11.8	10.1	1.7	1.19	-4.6	[-11.2, 2.0]	0.68	[0.37, 1.27]
ATET Adjusted	16.4	9.3	7.1	1.95	11.8	11.1	0.6	1.08	-6.4	[-14.2, 1.1]	0.72	[0.38, 1.37]
ATET AIPW Lasso	16.4	10.3	6.0	1.70	11.8	11.8	0.04	1.00	-6.0	[-13.8, 1.6]	0.59	[0.28, 1.22]
ATET IPW	16.4	9.5	6.9	1.87	11.8	14.7	-2.9	0.78	-9.8	[-21.4, 0.03]	0.42	[0.17, 1.11]
ATET IPWRA	16.4	9.3	7.1	1.91	11.8	11.7	0.1	1.01	-6.9	[-18.5, 0.6]	0.53	[0.19, 1.12]
ATET NNMATCH	16.4	11.6	4.7	1.49	11.8	16.1	-4.3	0.70	-9.0	[-18.3, 5.5]	0.47	[0.20, 2.00]
ATET PSMATCH	16.4	10.4	6.0	1.69	11.8	23.1	-11.2	0.46	-17.3	[-22.5, 3.5]	0.26	[0.14, 1.72]

C.L.I.M.B. = Community-based Life-changing Individualized Medically assisted evidence-Based treatment

RD = risk difference

OR = odds ratio

DRD = difference of risk differences

ROR = ratio of odds ratios

CI = confidence interval

ATET = average treatment effect on the treated

AIPW = augmented inverse-probability weighting

IPW = inverse probability weighting

IPWRA = inverse probability weighted regression adjustment

NNMATCH = nearest-neighbor matching

PSMATCH = propensity-score matching

* 95% CI percentile-based bootstrap 1,000 times

Table 4. Proportions of patients receiving post-detox treatments

	Pre-period			Post-period		
	Control	C.L.I.M.B.	p-value*	Control	C.L.I.M.B.	p-value*
	N=1,385	N=318		N=545	N=195	
Medication assisted treatment	390 (28.2)	131 (41.2)	<.001	153 (28.1)	71 (36.4)	0.030
Intensive outpatient treatment	303 (21.9)	115 (36.2)	<.001	146 (26.8)	46 (23.6)	0.382
Outpatient treatment	688 (49.7)	208 (65.4)	<.001	270 (49.5)	124 (63.6)	0.001

C.L.I.M.B. = Community-based Life-changing Individualized Medically assisted evidence-Based treatment

* p-values are based on chi-square tests.

Table 5. Intensive outpatient treatment services use in pre- and post-period and C.L.I.M.B. and comparison groups

	Pre-period				Post-period				Treatment Effect			
	C.L.I.M.B.	Control	RD	OR	C.L.I.M.B.	Control	RD	OR	DRD	95% CI*	ROR	95% CI*
ATET Unadjusted	36.2	21.9	14.3	2.02	23.6	26.8	-3.2	0.84	-17.5	[-26.3, -8.3]	0.42	[0.26, 0.66]
ATET Adjusted	36.2	23.3	12.9	1.91	23.6	24.4	-0.7	0.96	-13.6	[-23.7, -4.4]	0.42	[0.26, 0.67]
ATET AIPW Lasso	36.2	18.9	17.2	2.43	23.6	22.2	1.4	1.08	-15.9	[-25.3, -5.5]	0.45	[0.27, 0.78]
ATET IPW	36.2	19.0	17.2	2.42	23.6	19.7	3.9	1.26	-13.3	[-24.6, -2.3]	0.52	[0.28, 0.98]
ATET IPWRA	36.2	19.0	17.2	2.41	23.6	19.7	3.9	1.26	-13.3	[-25.2, -3.0]	0.52	[0.26, 0.97]
ATET NNMATCH	36.2	22.2	14.0	1.99	23.6	24.1	-0.5	0.97	-14.6	[-33.4, -2.3]	0.49	[0.18, 0.98]
ATET PSMATCH	36.2	22.0	14.2	2.01	23.6	22.1	1.5	1.09	-12.6	[-28.8, -1.5]	0.54	[0.21, 1.37]

C.L.I.M.B. = Community-based Life-changing Individualized Medically assisted evidence-Based treatment

RD = risk difference

OR = odds ratio

DRD = difference of risk differences

ROR = ratio of odds ratios

CI = confidence interval

ATET = average treatment effect on the treated

AIPW = augmented inverse-probability weighting

IPW = inverse probability weighting

IPWRA = inverse probability weighted regression adjustment

NNMATCH = nearest-neighbor matching

PSMATCH = propensity-score matching

* 95% CI percentile-based bootstrap 1,000 times

Figures



Figure 1

Patient selection criteria

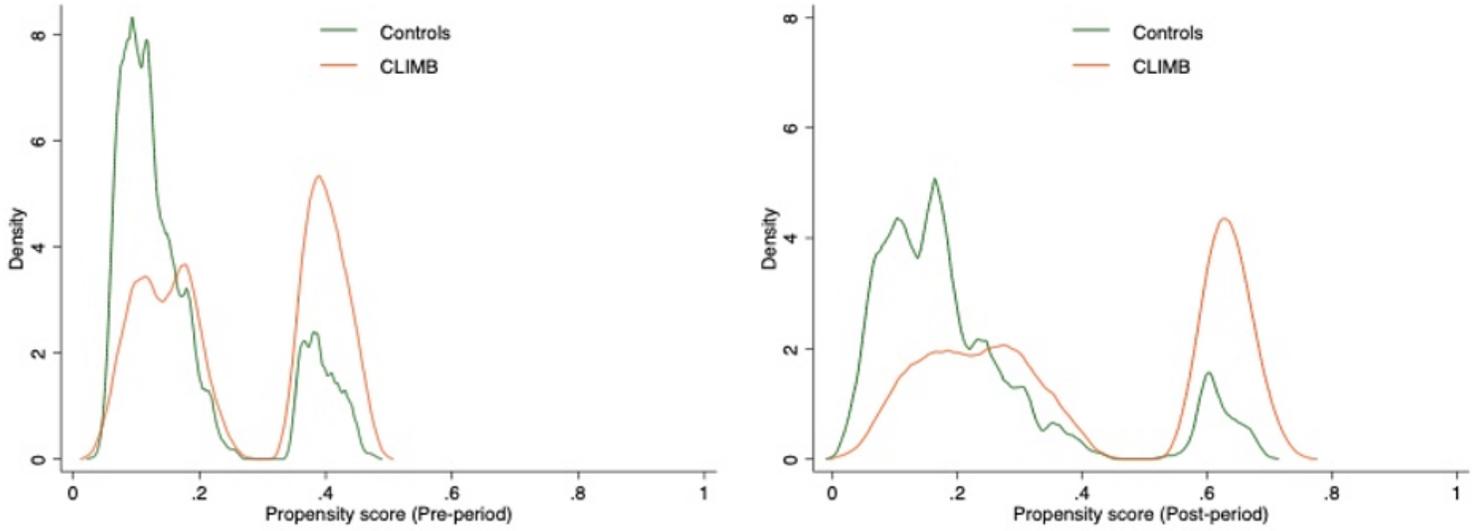


Figure 2

Propensity scores for participating in the pilot program in pre- and post-periods

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