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The association between medication for opioid use disorder and employment outcomes in the U.S.: The relevance of race and ethnicity

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1. Introduction

A common treatment option for opioid use disorder is medication-assisted treatment (MAT), also known as medication for opioid use disorder (MOUD), which combines the use of medications such as methadone, buprenorphine, or naltrexone with counseling and behavioral therapies (CDC, 2019; SAMHSA, 2021). Evidence demonstrates that compared to relapse-prevention treatments without medication, MOUD is more effective in reducing opioid use and increases the likelihood of retention in treatment (Fudala et al., 2003; Woody et al., 2008; Mattick et al., 2009; Krupitski et al., 2011; Weiss et al., 2011; Connery, 2015). Evidence is less consistent but suggests that MOUD, particularly methadone maintenance treatment (MMT) (instead of detoxification programs) and higher doses of MMT, is associated with lower rates of drug-related HIV risk behaviors, mortality, and criminality (Fletcher and Battjes, 1999; Ward et al., 1998; Sees et al., 2000; Faggiano et al., 2003; Fullerton et al., 2014). The positive physical, mental, and social outcomes associated with the use of MOUD suggest that employment outcomes may be improved for patients with MOUD relative to those without MOUD.

Surprisingly, however, only limited research has been conducted on the relationship between MOUD use and employment outcomes. Notably, several studies conducted in this arena have identified no discernible effects on employment outcomes (Sees et al., 2000; Kinlock et al., 2009; Coviello et al., 2010; Crits-Christoph, 2015; Maglione et al., 2018). On the other hand, Richardson and colleagues found that among a community-recruited Canadian cohort of people who inject drugs, individuals enrolled in methadone maintenance therapy (MMT) were less likely to move into regular employment than those not given MMT treatment (Richardson et al., 2012). They conjectured that this counterintuitive finding could be attributed to several plausible explanations including but not limited to: the goals of MMT toward stabilized maintenance, in which the initiation of employment may be unlikely to follow the trajectory of employment activities associated with non-MMT modalities; the impairment of MMT on cognitive functions (Darke et al., 2000); the lower levels of education and work histories that may be more common among individuals on MMT than those not on MMT (Svikis et al., 2012); and the presence of on-going drug use by individuals enrolled in MMT (Barnas et al., 1992; Demaria et al., 2000); all of which may affect the capacity to undertake employment.

Other factors, such as bias and discrimination, may also contribute to the difficulties individuals on MOUD potentially encounter in their efforts to secure employment. Despite the evidence of MOUD's effectiveness in reducing dependence on illicit opioids and in reducing high-risk behaviors, its use remains highly stigmatized (Wakeman and Rich, 2018; Allen et al., 2019; Vestal, 2016; Madden, 2019). Because of the stigma associated with MOUD, individuals on MMT are more likely to report experiences with racial discrimination in healthcare settings than their counterparts not receiving MMT (Pro and Zaller, 2020). While research has identified employer and co-worker bias and stigma among the various barriers confronting those using MOUD in their efforts to seek or maintain employment (French et al., 1992; Lones et al., 2017), the extent to which this bias undermines employment outcomes for individuals on MOUD is understudied. Additionally, research indicates that Blacks are more likely than Whites to be drug tested under clinical care settings (Becker et al., 2011; Gaither et al., 2018) and Blacks are more likely to be employed in workplaces that perform drug-testing (Becker et al., 2014). However, what remains unclear is the degree to which MOUD-related discrimination affects the employment status of individuals who must undergo drug-testing as a condition of initiating or maintaining work even though individuals who rely on MOUD are currently protected by the American with Disabilities Act (ADA).

Given the evidence of discrimination against individuals receiving MOUD and the racial/ethnic disparities in drug testing practices, surprisingly, research on the association between use of MOUD and employment outcomes has not investigated the potential impacts of race/ethnicity in shaping employment outcomes among those who receive MOUD. Research and data have consistently documented the existence of disparities in the labor market outcomes between non-Hispanic Whites and racial minorities, particularly Blacks (Pager and Shepherd 2008; U.S. Bureau of Labor Statistics, 2020) - disparities that cannot be solely attributed to racial/ethnic differences in education or skill set. Field experiments and qualitative interviews have long highlighted employers' willingness to discriminate against racial minorities (Turner et al., 1991; Bendick et al., 1994; Pager, 2003; Bertrand and Mullainathan, 2004; Pager et al., 2009; Pager and Karafin, 2009). Given

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ongoing discrimination in the labor market, the stigma associated with the use of MOUD may compound, for racial minorities, existing obstacles to securing employment.

Furthermore, racial/ethnic disparities in treatment outcomes may have implications for how racial minorities on MOUD experience employment relative to their White counterparts. Research has found racial/ethnic disparities in treatment outcomes for opioid and other substance use disorders. Analyses of state level data and data on opioid users in large metropolitan areas show that racial minorities are less likely than Whites to complete treatment (Arndt et al., 2013; Stahler and Mennis, 2018). Blacks are also less likely than Whites to experience improvement in substance use outcomes (including use of opioids) upon discharge (Sahker et al., 2020). While these studies recognize that individual-level factors (e.g. individual economic resources) potentially affect treatment completion and substance use improvement, they also acknowledge the structural or external factors, such as the geographic variation in policies and the availability of certain services, that may contribute to racial/ethnic disparities in treatment outcomes. For example, state-wide variation in the provision of recovery support services, such as job training, housing, food, and childcare, might produce racial/ethnic disparities in treatment outcomes if there are racial/ethnic differences in the need, effectiveness, and availability of such services (Arndt et al., 2013). Furthermore, differences in the availability of such services in high minority density cities may also contribute to racial/ethnic disparities in treatment completion (ibid.). According to Stahler and Mennis, racial/ethnic differences in treatment completion vary geographically, and location may be "a proxy for variability in policy and regional program practice and may intersect with other factors (such as)… variations in drug supply and drug control efforts, differences in insurance coverage, and characteristics of SUD treatment programs that may be unique to individual metropolitan areas" and hence contribute to racial/ethnic disparities (2018 pg. 174).

Also, recent evidence suggests that clients given MOUD are less likely to complete treatment than their counterparts not assigned MOUD (Askari et al., 2020), and this likelihood may be reduced further by continued use of illicit drugs (White et al., 2014). To the extent that non-completion of treatment and continued use of illicit substances negatively affect employment outcomes, the association between MOUD and employment activity may differ by race/ethnicity. Given the evidence concerning racial disparities in treatment outcomes and the stigma associated with MOUD use, which may exacerbate discrimination against racial minorities in the labor market, we 1) revisit key questions concerning the relationship between MOUD and employment outcomes and 2) investigate the extent to which race/ethnicity mediates the relationship between MOUD and employment outcomes.

2. Material and methods

2.1. Data

The primary data set for the analysis is the Treatment Episode Data Set on discharges (TEDS-D), maintained by the U.S. Substance Abuse and Mental Health Services Administration (Substance Abuse and Mental Health Services Administration October 15, 2020). Additionally, data on state unemployment rates obtained from the U.S. Bureau of Labor Statistics' website were merged to the data provided by TEDS-D.[1] The TEDS system "compiles client-level data for substance abuse treatment admissions from state agency data systems, (which) collect data from facilities about their admissions to treatment and discharges from treatment." (Substance Abuse and Mental Health Services Administration May 1, 2021). The two major components of the TEDS system are admission data (TEDS-A) and discharge data (TEDS-D). TEDS-A contains data on the demographic, clinical, and substance use characteristics of clients admitted to treatment facilities that report to state administrative data systems. TEDS-D retains the information held by TEDS-A but also includes data on type of service at discharge, length of stay in treatment, and reason for discharge. The information provided by states annually and then standardized by the TEDS system only pertains to admissions to and discharges from treatment centers that are publicly funded.

While each annual data set from the TEDS system contains an exceptionally large number of observations, our sample included a fraction of the data due to several constraints. SAMHSA has been providing TEDS discharge data since 2006, but we combined discharge data only from 2015-2018 since information on employment status at discharge was not available until 2015. The flow diagram on subject inclusion and exclusion in Fig. 1 shows how the final sample was determined.

Additionally, the map of the U.S. states in Fig. 2 highlights the states that were excluded from the analyses along with a rationale for their exclusion.

2.2. Key variables

While looking at employment status at discharge may reveal interesting associations between MOUD and employment outcomes, such information is limited since it ignores potential changes in employment status from admission to discharge. For example, if the probability of a switch from unemployment during admission to employment at discharge increases for those on MOUD even if their employment conditions at discharge are similar to those of non-MOUD clients, this suggests different conclusions about MOUD than those uncovered by an exclusive focus on employment status at discharge. Although we considered the effect of MOUD on employment status at discharge (see Supplemental Information, Appendix A), we are primarily interested in potential changes in the employment circumstances of those discharged from treatment. Thus, we created two dependent variables to reflect this emphasis. One of the dependent variables considers whether a client became employed (on a part-time or full-time basis) or remained unemployed/out of the labor force at discharge when the client was not working at the time of admission.[2] The other variable considers whether the client became unemployed/left the labor force or remained employed at discharge when the client was initially employed during admission.

We are interested in how three variables predict employment outcomes. The first independent variable of interest is MOUD use, a binary variable indicating whether the use of medication assisted treatment, such as methadone, buprenorphine, or naltrexone, was part of the client's treatment plan. The second independent variable is race/ethnicity, a variable with three categories –Black, Hispanic, or White (non-Hispanic White). The third independent variable accounts for the interaction between race/ethnicity and MOUD use. We included this race/ethnicity-MOUD interaction term to determine 1) the extent to which the association between MOUD and employment outcomes is consistent across racial/ethnic groups and 2) the degree to which racial disparities widen or narrow with MOUD use, especially among those

[1] Specifically, we use the *merge* function in STATA to add annual state unemployment rates to the TEDS data set. The merge function in STATA adds new variables from a second data set to existing observations in the main data set. In this study, we added the annual state unemployment rates as the new variable, so that each observation in our main data set (TEDS) is associated with an annual state unemployment rate, which would reflect the state where the individual was discharged as well as the year of discharge (e.g. the observation of a client who was discharged in California in 2015 would be associated with California's unemployment rate in 2015).

[2] We include individuals not in the labor force as part of this variable primarily because this group covers those who were not looking for work in the past 30 days, a decision that might be impacted by the type of treatment undertaken. Additionally, perhaps the decision to remain in the labor force rather than to retire might be impacted by treatment outcomes. In one of the sensitivity analyses (Appendix H), we exclude those not in the labor force from the dependent variable.

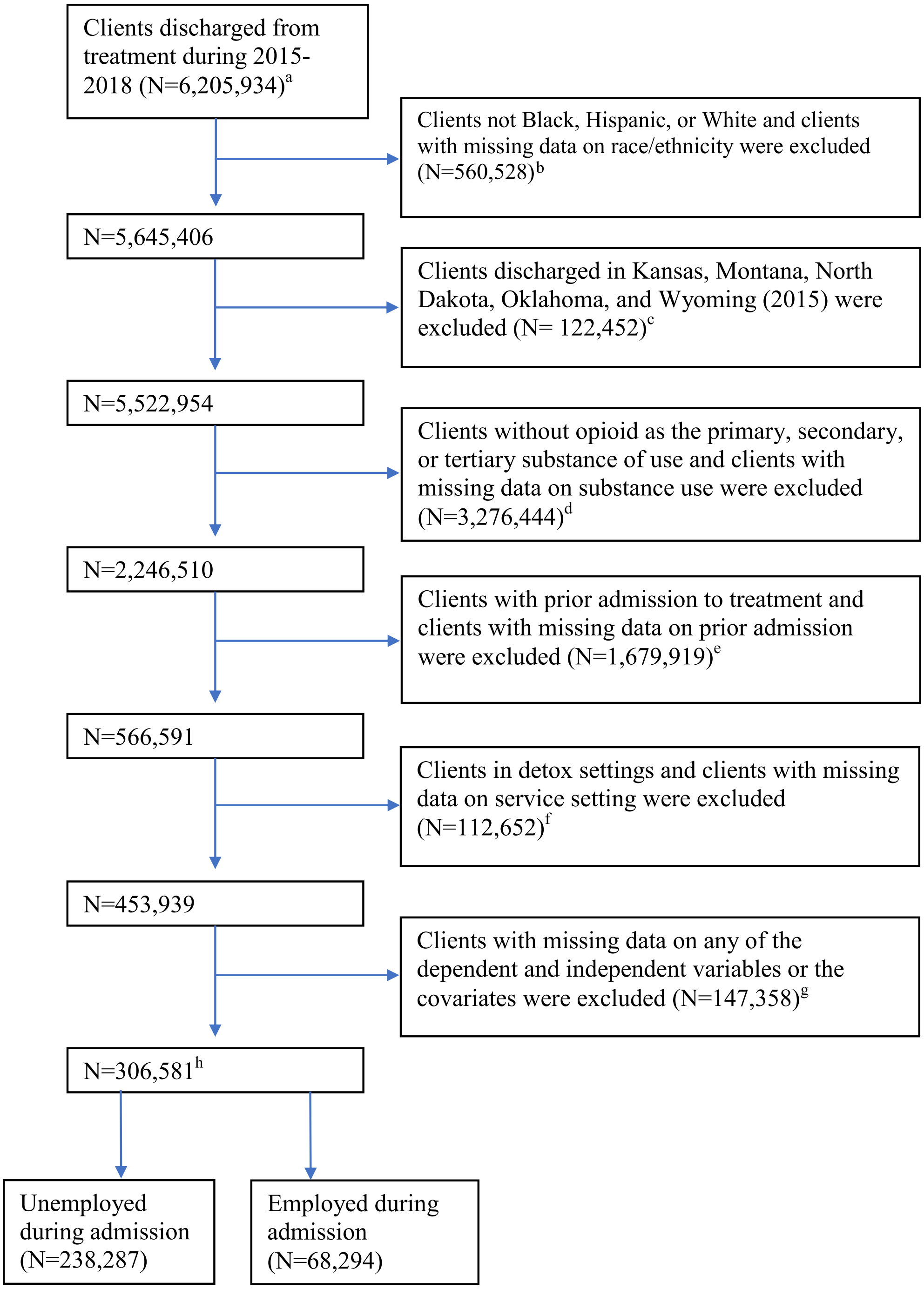

Fig. 1. Subject Inclusion/Exclusion Flow Diagram
a. Information on employment status at discharge was not available until 2015. The initial sample included clients discharged from treatment between 2015 and 2018 who had data points on any of the relevant variables.
b. Clients who identified as Asian, Native American, multiracial, or other race were excluded because these clients constituted a much smaller portion of the TEDS data.
c. Clients discharged from treatment in these states were excluded because from 2015 to 2018, these states either reported no clients on MOUD treatment or had missing information on MOUD use.
d. Only clients who reported opioid as their primary, secondary, or tertiary substance of use were included because we are primarily interested in medication assisted treatment as an intervention for opioid use disorder.
e. TEDS data represents admissions and discharges and not individual clients. Thus, to circumvent the issue of repeated observations for the same individual, the sample was restricted to individuals with no reported history of prior treatment. Because all clients in Indiana (2015–2017) and South Carolina had a history of prior admission and information on prior treatment was missing in Wisconsin, discharges in these states were excluded.
f. We excluded clients whose treatment occurred in detoxification-only settings, which is consistent with the methodologies of other studies (Solomon et al., 2022; Stahler and Mennis, 2020).
g. The final dataset was restricted to only observations with nonmissing data for all covariates and outcomes.
h. The final dataset was divided into two samples defined by the client's employment status at the time of admission (employed vs. unemployed/not in labor force)

who made gains in employment and those who became unemployed or left the labor force.

2.3. Covariates

Other factors may also affect employment status and thus mediate MOUD's association with employment outcomes. These variables include clinical and substance use considerations. Thus, we included as a covariate in our statistical models the *number of days in treatment*, a seven-category variable ranging from 0 days to more than a year in treatment. Another covariate in our analysis is the *reason for discharge*, a seven-category variable that includes, but is not limited to, information about whether the client completed treatment, dropped out, transferred to another facility, or had treatment terminated by the facility. Other variables we incorporated in the analysis are whether *heroin was reported as the primary substance* of use at the time of admission, whether the *illicit use of substances on a daily basis* was reported at time of discharge, and whether the client was at the time of admission *referred to treatment by the criminal justice system,* which includes but is not limited to sources such as the courts, the probation and parole system, diversionary and DUI/DWI programs, and prison.

Demographic characteristics constitute another set of covariates that potentially affect employment outcomes. Thus, our analysis included *age*, a variable with five categories: 18–29 years, 30–39 years, 40–49 years, 50–64 years, and 65 years or older. The analysis also considered the covariates of *sex* (male or female), *education* (the lack of a high school degree, the attainment of a high school degree or its equivalent, the completion of 13–15 years of education, or the com-

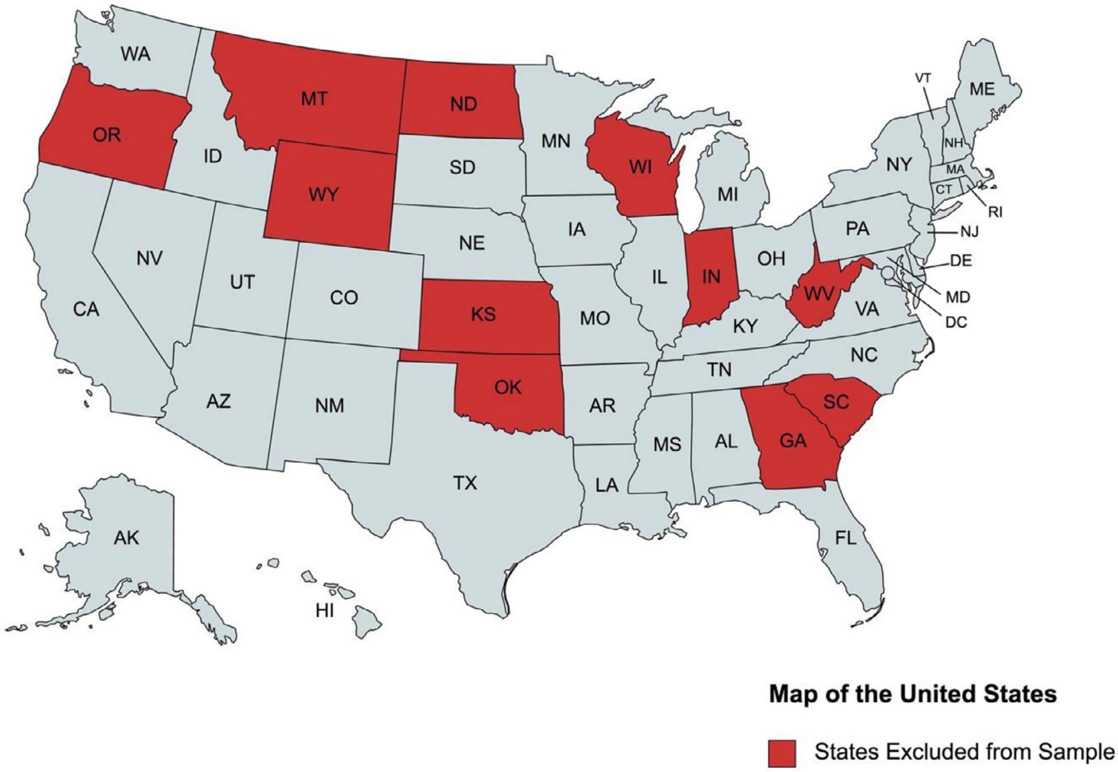

Fig. 2. States Excluded from Analysis
We excluded observations in Kansas, Montana, North Dakota, Oklahoma, and Wyoming (only in 2015) from the sample because these states reported no MOUD use from 2015 to 2018. This may either reflect a reporting error or the absence of MOUD provision.
We also excluded observations from Indiana (only from 2015 to 2017), South Carolina, and Wisconsin because all clients from Indiana (2015–2017) and South Carolina were reported with prior admissions to treatment centers, and prior admission information was missing from Wisconsin's data.
Georgia, Oregon, and West Virginia did not provide information on treatment discharges to the TEDS system from 2015 to 2018.
*Map created with mapchart.net

pletion of 16 or more years of education), and *employment status during admission*, recoded as whether the client was employed on a full-time or part-time basis or not working (unemployed or out of the labor force).

Place-level and other factors may also affect the association between MOUD and employment outcomes. Therefore, the analysis considered *state unemployment rates*, specifically the 2015-2018 unemployment rates of the states where clients were discharged from treatment. We obtained these rates from the U.S. Bureau of Labor Statistics (2016, 2021). The analysis also incorporated the annual *percentages of MOUD clients in states* where clients were discharged from treatment. We calculated these percentages from the information provided by TEDS data set. These percentages serve as an imperfect proxy for state-level policy contexts, which may impact the likelihood of taking up MOUD treatment as well as public receptiveness toward MOUD use.[3] Finally, we also took into consideration the *year* client was discharged from treatment (2015, 2016, 2017, 2018). Table 1 reports the variables' averages and frequencies by race/ethnicity.

[3] It is possible that state percentages of MOUD clients may reflect varying levels of stigma associated with MOUD use. Perhaps in states with higher percentages of clients seeking MOUD treatment, less stigma would be associated with MOUD use than in states with lower levels of MOUD utilization, and levels of stigmatization may affect employment outcomes. However, it is more likely that the covariate of state percentages of MOUD use is capturing variation in the political/policy context among states, and stigmatization may be a secondary proxy result.

2.4. Statistical analysis

Because our dependent variables are binary, we used logistic regressions to assess the associations among race/ethnicity, MOUD intervention, and employment outcomes. Specifically, we used a multi-level logistic regression, with states treated as random effects to account for variability among states even after controlling for measurable state-level characteristics such as unemployment rates. We divided the overall data set into two samples: clients who at the time of admission were employed and those who were unemployed (which included being out of the labor force). We ran a logistic regression on each sample to determine whether among clients who were reported as not working during admission, MOUD predicted being employed by the time of discharge and whether among those employed during admission, MOUD predicted lack of employment by the time of discharge. To avoid problems of collinearity, we excluded the variable on employment status at admission since this information was already reflected in our dependent variables of becoming employed or unemployed/leaving the labor force. Because analyses of large data sets are more likely than smaller data sets to yield findings of statistically significant group differences, we reported the findings with 99% confidence intervals and assessed statistical significance at the $p<0.001$ level, which is consistent with the methodology of previous studies (Pro et al., 2020; Krawczyk et al., 2017).

We also performed sensitivity analyses to ensure that our results were consistent across different considerations. In one analysis, we assessed the association between MOUD use and employment status at discharge and hence did not separate the data set into two samples. In-

Table 1
Frequencies and means by race/ethnicity.

Variable	Values	Black (*N*=30,549)	Hispanic (*N*=31,785)	White (*N*=244,247)
Employment Status at Discharge	Employed (Full-time and part-time)	5296 (17.34%)	7975 (25.09%)	63,760 (26.10%)
	Unemployed/Not in Labor Force	25,253 (82.66%)	23,810 (74.91%)	180,487 (73.90%)
Unemployed at Admission	Becomes Employed at Discharge	1712 (6.57%)	2617 (10.40%)	13,267 (7.09%)
	Remains Unemployed at Discharge	24,357 (93.43%)	22,552 (89.60%)	173,782 (92.91%)
Employed at Admission	Becomes Unemployed at Discharge	896 (20.00%)	1258 (19.01%)	6705 (11.72%)
	Remains Employed at Discharge	3584 (80.00%)	5358 (80.99%)	50,493 (88.28%)
MOUD (MAT)	Yes	10,832 (35.46%)	11,162 (35.12%)	56,898 (23.30%)
	No	19,717 (64.54%)	20,623 (64.88%)	187,349 (76.70%)
Days in Treatment	30 Days or less	13,356 (43.72%)	11,054 (34.78%)	131,445 (53.82%)
	31–60 Days	4120 (13.49%)	4627 (14.56%)	28,733 (11.76%)
	61–90 Days	2765 (9.05%)	3105 (9.77%)	18,974 (7.77%)
	91–120 Days	1929 (6.31%)	2340 (7.36%)	13,364 (5.47%)
	121–180 Days	2369 (7.75%)	2785 (8.76%)	15,741 (6.44%)
	181–365 Days	3198 (10.47%)	3768 (11.85%)	19,844 (8.12%)
	More than 1 Year	2812 (9.20%)	4106 (12.92%)	16,146 (6.61%)
Reason for Discharge	Completed Treatment	6174 (20.21%)	9390 (29.54%)	64,142 (26.26%)
	Dropped Out	9929 (32.50%)	9464 (29.78%)	54,291 (22.23%)
	Terminated	3490 (11.42%)	2360 (7.42%)	16,314 (6.68%)
	Transferred	8336 (27.29%)	7841 (24.67%)	92,670 (37.94%)
	Incarcerated	756 (2.47%)	905 (2.85%)	4159 (1.70%)
	Death	138 (0.45%)	129 (0.41%)	621 (0.25%)
	Other	1726 (5.65%)	1696 (5.34%)	12,050 (4.93%)
Age	18-29	7867 (25.75%)	13,011 (40.93%)	108,749 (44.52%)
	30-39	6388 (20.91%)	9819 (30.89%)	85,937 (35.18%)
	40-49	6924 (22.67%)	5174 (16.28%)	31,067 (12.72%)
	50-64	8711 (28.51%)	3564 (11.21%)	17,620 (7.21%)
	65 and older	659 (2.16%)	217 (0.68%)	874 (0.36%)
Sex	Male	19,942 (65.28%)	21,111 (66.42%)	131,349 (53.78%)
	Female	10,607 (34.72%)	10,674 (33.58%)	112,898 (46.22%)
Education	Less than HS Degree	9911 (32.44%)	11,706 (36.83%)	55,447 (22.70%)
	High School Diploma	14,537 (47.59%)	14,387 (45.26%)	122,693 (50.23%)
	13-15 Years	4926 (16.12%)	4867 (15.31%)	52,889 (21.65%)
	16 and More Years	1175 (3.85%)	825 (2.60%)	13,218 (5.41%)
Employed during admission	Yes	4480 (14.66%)	6616 (20.81%)	57,198 (23.42%)
	No	26,069 (85.34%)	25,169 (79.19%)	187,049 (76.58%)
Heroin as Primary Substance Use	Yes	11,577 (37.90%)	11,995 (37.74%)	108,407 (44.38%)
	No	18,972 (62.10%)	19,790 (62.26%)	135,840 (55.62%)
Criminal Justice	Yes	6355 (20.80%)	8,752 (27.54%)	63,153 (25.86%)
	No	24,194 (79.20%)	23,033 (72.46%)	181,094 (74.14%)
Daily Use of Substance at Discharge	Yes	14,340 (46.94%)	10,488 (33.00%)	91,569 (37.49%)
	No	16,209 (53.06%)	21,297 (67.00%)	152,678 (62.51%)
State Unemployment Rate	0-1.00	0.047	0.047	0.046
State MOUD Rate	0-1.00	0.252	0.3	0.231
Discharge Year	2015	6521 (21.35%)	6983 (21.97%)	56,217 (23.02%)
	2016	6572 (21.51%)	7079 (22.27%)	57,512 (23.55%)
	2017	9020 (29.53%)	8836 (27.80%)	71,242 (29.17%)
	2018	8436 (27.61%)	8887 (27.96%)	59,276 (24.27%)

formation about employment status during admission was included as a covariate in the model. Additionally, we modeled a three-way interaction among MOUD use, race/ethnicity, and days in treatment to explore whether any observed differences in association between MOUD use and employment across racial/ethnic groups simply reflected racial/ethnic differences in length of treatment, which might serve as a proxy for severity of substance use and/or the presence of additional hurdles to treatment. To further investigate whether racial/ethnic differences mostly reflected differences in treatment outcomes and hence disparities in employment, we also specified another model with a three-way interaction variable comprising of MOUD use, race/ethnicity, and reasons for discharge from treatment as well as a model accounting for a three-way interaction among MOUD use, race/ethnicity, and the frequency of illicit drug use upon discharge. To investigate the extent to which group differences reflected racial/ethnic disparities in experiences with the criminal justice system and hence disparities in employment, we created a model accounting for a three-way interaction among MOUD use, race/ethnicity, and the referral to treatment by the criminal justice system. Furthermore, in another analysis, we did not exclude clients with a history of prior admission (treating history of prior admission as a covariate). Because the final data set was restricted to only observations with nonmissing data for all covariates and outcomes, we employed the method of multiple imputation by chained equations to deal with the problem of missing data. Finally, we modified the dependent variable to exclude admissions and discharges categorized as not being in the labor force. These additional analyses yielded results that were mostly similar to those of the original analyses (see Sensitivity Analyses in Supplemental Information).

3. Results

3.1. Unemployed during admission

When the sample was restricted to those who were unemployed during admission, the odds of becoming employed rather than remaining unemployed at discharge were 8.6% lower for those using MOUD than for those without MOUD (aOR, 0.914; 99% CI, 0.861–0.970; $P<0.000$). This finding, however, does not show whether the association between MOUD and employment is similar across racial/ethnic groups or whether disparities, if any, increase or decrease with the use of MOUD. Thus, we extended our models to include an interaction term

Table 2
Association among MOUD, race/ethnicity, and becoming employed at discharge.

Unemployed/Not in Labor Force at Admission	Independent Association			Interaction Association		
	aOR	99% CI	p-value	aOR	99% CI	*p*-value
MOUD	0.914*	[0.861–0.970]	0.000	—	—	—
Black|MOUD	—			0.638*	[0.562–0.723]	0.000
Hispanic|MOUD	—			0.744*	[0.667–0.829]	0.000
Black|No MOUD	—			0.867*	[0.788–0.953]	0.000
Hispanic|No MOUD	—			0.912	[0.842–0.987]	0.003
MOUD|Black	—			0.716*	[0.618–0.831]	0.000
MOUD|Hispanic	—			0.794*	[0.700–0.901]	0.000
MOUD|White	—			0.974	[0.912–1.039]	0.289

Dependent variable is whether the client became employed at discharge when unemployed/not in the labor force (NLF) at admission or remained unemployed/out of the labor force. Results reported are adjusted odds ratio from a multilevel random effects logistic regression. Covariates were included in the model, but the results are not reported here. Reference categories are White and No MOUD. Black | MOUD refers to the odds of employment for Blacks relative to Whites conditional upon receipt of MOUD (among MOUD clients). MOUD | Black refers to the odds of employment for MOUD clients relative to non- MOUD clients conditional upon being Black (among Black clients).

* $p<0.001$

to assess how race/ethnicity and MOUD may impact the other variable's respective association with becoming employed.

When we considered the impact of race/ethnicity for unemployed admissions who were assigned MOUD, we observed important disparities. Among Whites, the odds of shifting from unemployment to employment rather than remaining unemployed were 2.6% less for clients on MOUD than for those without MOUD, a difference that was not statistically significant (aOR, 0.974; 99% CI, 0.912–1.039; $p<0.289$). Among Black admissions, however, the odds of becoming employed rather than remaining unemployed were 28.4% less for admissions who were assigned MOUD relative to those who were not assigned MOUD (aOR, 0.716; 99% CI, 0.618–0.831; $p<0.000$). A similar pattern was observed among Hispanics. For Hispanics, the odds of becoming employed rather than remaining unemployed were 20.6% lower for clients with MOUD than for Hispanics without MOUD (aOR, 0.794; 99% CI, 0.700–0.901; $p<0.000$).

Among the unemployed who were assigned MOUD, we observed a significant gap between Black outcomes and White outcomes, with the odds of becoming employed being 36.2% less for Blacks than for Whites (aOR, 0.638; 99% CI, 0.562–0.723; $p<0.000$). Among unemployed Hispanics who were assigned MOUD, the odds of becoming employed were 25.6% less than those for unemployed Whites (aOR, 0.744; 99% CI, 0.667–0.829; $p<0.000$). Among those who were unemployed at admission and did not receive MOUD as part of their treatment plan, Blacks were 13.3% less likely to become employed than Whites (aOR 0.867; 99% CI, 0.788–0.953; $p<0.000$). Meanwhile, the difference in likelihood of employment between unemployed Hispanics and unemployed Whites who did not receive MOUD was not statistically significant (aOR, 0.912; 99% CI, 0.842–0.987; $P<0.003$) Table 2.

3.2. Employed during admission

When the sample was limited to clients who were employed during admission, the odds of becoming unemployed or leaving the labor force rather than remaining employed were 6.0% less for admissions given MOUD than for admissions not given MOUD. This difference was not statistically significant (aOR, 0.940; 99% CI, 0.866–1.020; $P<0.049$).

Consideration of the role of race/ethnicity, however, highlighted important patterns. For Whites who were admitted for treatment while employed, MOUD had a positive impact on their ability to remain employed at discharge. Indeed, among White admissions, the odds of becoming unemployed or leaving the labor force were 10.8% less for clients who were assigned MOUD as part of their treatment plans than for those who were not (aOR, 0.892; 99% CI, 0.816–0.975; $p<0.001$). Among employed Black and Hispanic admissions, meanwhile, MOUD did not play a positive role in employment outcomes at discharge. In both cases, we observed higher odds of becoming unemployed at discharge for those who were assigned MOUD relative to Blacks and Hispanics who were not assigned MOUD, but these differences were not statistically significant (aOR, 1.135; 99% CI, 0.912–1.412; $P<0.135$; aOR, 1.106; 99% CI, 0.924–1.325; $p<0.148$).

However, racial/ethnic disparities were particularly notable in our comparison of the outcomes of employed White admissions who were assigned MOUD with those of their Black and Hispanic counterparts. Compared to Whites, the odds of becoming unemployed were 42.9% greater for Blacks (aOR, 1.429; 99% CI, 1.196–1.707; $P<0.000$). The gap between employed Hispanic and employed White clients who were assigned MOUD was also substantial, with the odds of becoming unemployed being 25.3% higher for Hispanics than for Whites (aOR, 1.253; 99% CI, 1.082–1.451; $P<0.000$). Among Black and Hispanic admissions who were not assigned MOUD, the odds of becoming unemployed were higher for both Blacks and Hispanics relative to Whites. These findings, however, were not statistically significant (aOR, 1.123; 99% CI, 0.969–1.301; $p<0.043$; aOR, 1.010; 99% CI, 0.890–1.146; $P<0.841$) Table 3.

4. Discussion

When we did not consider the interaction of race/ethnicity and MOUD use, we found results that were somewhat consistent with those of past studies not identifying notable associations between MOUD use and employment. However, when we considered the role of race/ethnicity in shaping employment outcomes, we found that for Black and Hispanic admissions, being treated with MOUD options lowered the likelihood that they would become employed at discharge. Meanwhile employed White admissions who were assigned MOUD were less likely to become unemployed upon discharge than Whites who were not assigned MOUD. This benefit did not accrue to employed Black and Hispanic admissions given MOUD, who were neither more nor less likely to become unemployed than those not assigned MOUD. Moreover, Blacks and Hispanics given MOUD were substantially more likely than their White counterparts to become unemployed at discharge.

4.1. Potential explanations

Blacks and Hispanics may be less likely than Whites to benefit from MOUD in terms of employment outcomes for various reasons. As previously mentioned, past studies have found that racial minorities are less

Table 3
Association among MOUD, race/ethnicity, and becoming unemployed at discharge.

Employed at Admission	Independent Association			Interaction Association		
	aOR	99% CI	p-value	aOR	99% CI	p-value
MOUD	0.940	[0.866–1.020]	0.049	—	—	—
Black|MOUD	—			1.429*	[1.196–1.707]	0.000
Hispanic|MOUD	—			1.253*	[1.082–1.451]	0.000
Black|No MOUD	—			1.123	[0.969–1.301]	0.043
Hispanic|No MOUD	—			1.010	[0.890–1.146]	0.841
MOUD|Black	—			1.135	[0.912–1.412]	0.135
MOUD|Hispanic	—			1.106	[0.924–1.325]	0.148
MOUD|White	—			0.892*	[0.816–0.975]	0.001

Dependent variable is whether the client became unemployed/left labor force at discharge when employed at admission or remained employed. Results reported are adjusted odds ratio from a multilevel random effects logistic regression. Covariates were included in the model, but the results are not reported here.

* $p<0.001$

likely than Whites to complete treatment (Arndt et al., 2013; Stahler and Mennis, 2018) and Blacks are less likely than Whites to experience improvement in substance use outcomes (Sahker et al., 2020). To the extent that racial/ethnic differences in treatment outcomes negatively affect employment, the association between MOUD and employment activity may differ by race/ethnicity. However, this study not only controlled for treatment outcomes but also considered in the sensitivity analyses the effect of MOUD conditional upon the interaction of race/ethnicity and various indicators of treatment outcomes and still found the persistence of racial/ethnic differences in employment outcomes (see Supplemental Information Appendices C & D). Thus, it appears that racial differences in treatment outcomes do not largely explain racial/ethnic disparities in the relationship between MOUD and employment.

Perhaps interactions with the criminal justice system may be contributing to racial disparities in employment outcomes for those on MOUD. For drug-related crimes, Blacks and Hispanics are incarcerated for longer periods of time than are Whites, and racial disparities in the criminal justice system are exacerbated when other forms of supervision, such as parole and probation, are considered (Alexander, 2012). While we controlled for whether the client was referred to treatment by the criminal justice system and still found a statistically significant interaction of race and MOUD use on employment outcomes, we also modeled a three-way interaction among race, MOUD use, and referral by the criminal justice system to determine their joint effect on employment outcomes. In this sensitivity analysis, we actually found racial disparities among those on MOUD treatment and whose referral source was ***outside*** the criminal justice system but found no statistically significant racial disparities among those on MOUD and referred to treatment by the criminal justice system (see Appendix E). Given the significantly larger proportion of clients referred to treatment by sources not associated with the justice system and given the results produced from controlling for the independent effect of justice system referrals along with the consideration of the interaction effects of such referrals with race and MOUD status, the main findings here are not primarily explained by experiences with the criminal justice system.

As mentioned before, bias and discrimination against those on MOUD may also be driving racial/ethnic disparities in employment outcomes. However, the extent to which bias undermines the employment outcomes of individuals on MOUD has not been adequately studied. Currently, individuals who rely on MOUD are protected under the American with Disabilities Act (ADA), but evidence of discrimination against these individuals has been documented. The U.S. Equal Employment Opportunity Commission (EEOC) has, in the past, filed several anti-discrimination lawsuits against employers who automatically disqualified individuals from further consideration for a job or terminated their employment because the individual was taking legally prescribed medication for their substance use disorder (EEOC v. Volvo Group North America, LLC, 2017; EEOC v. Appalachian Wood Products, Inc., 2018; EEOC vs. Foothills Child Development Center Inc., 2018; EEOC v. Professional Transportation, Inc., 2020). Furthermore, the ADA allows employers to make individualized assessments to determine whether the individual can carry out essential job duties if given reasonable accommodations, but these individualized assessments may give employers leeway to discriminate against those on MOUD especially if "courts continue to misapply a narrow interpretation that could in a way allow for legal prescription drug use to fall outside of coverage" (Palmer, 2019 pg. 140). Racial/ethnic minorities already face racial discrimination in the workplace, and hence employers may be even less sympathetic to racial minorities on MOUD than to their White counterparts. Future studies should not only continue to investigate the extent to which individuals on MOUD encounter workplace bias but also look at how federal, state, and local anti-discrimination laws can strengthen the ADA's protection of individuals on MOUD and ameliorate the racially/ethnically disparate impact of MOUD on employment outcomes.

4.2. Additional policy implications

Furthermore, research should investigate how racial minorities, relative to Whites, benefit from therapeutic workplace intervention programs, employment programs where participants are paid to undertake job-skills training in the first phase and then take on actual employment in the second phase, all while being incentivized to remain drug-free. Such programs in conjunction with MMT programs do not cost more than other treatment programs (Knealing et al., 2008), and thus future studies should not only continue to assess the impact of such programs on employment outcomes, which has been shown to be positive (Holtyn et al., 2020; 2021), but also evaluate how these programs may improve the employment prospects of individuals on MOUD, especially racial minorities. Such assessments will provide valuable policy-relevant information concerning drug-treatment programs.

4.3. Limitations

This study has several important limitations. Because we restricted the analysis to include only those without a history of prior admission to a treatment center, the results may not be generalizable to those with reported histories of prior admission.[4] Furthermore, the study must acknowledge that being employed may affect access to MOUD. Thus, there is some uncertainty about how the association between employment status at admission and MOUD utilization bears upon the relationship

[4] In one of the sensitivity analyses (Appendix F), we include observations with prior admissions but add in the statistical model a covariate for whether the client had a history of prior admission. The results of this analysis are consistent with the main findings.

between MOUD utilization and employment status at discharge. This concern would be especially aggravated if we only considered employment status during discharge and simultaneously failed to control for employment status during admission. We addressed this issue by incorporating admission employment information in our models and by considering shifts in employment status over the course of treatment. Another limitation is that the TEDS data set contains information only on publicly funded treatment centers. Treatment in publicly funded centers may affect the impact of employment on MOUD access and/or the impact of MOUD treatment on employment status. Thus, the relationship between MOUD treatment and employment status for individuals in publicly funded centers may not be generalizable to individuals in other types of treatment facilities. We also recognize that this study is limited to three racial/ethnic groups and does not include other important factors that might affect the relationship between MOUD use and employment status. Thus, future work should investigate the impacts of MOUD for other groups such as Asian Americans and Native Americans. Future work should also look at how individual-level factors such as acculturation and resilience and factors that potentially reflect systemic bias (such as poverty rates among different groups in different states) affect the relationship between MOUD treatment and employment status.

Additionally, because state-level policy/political environments may affect the association between MOUD use and employment, research on this topic may benefit from the insights of political science scholarship. Political scientists have developed, critiqued, and refined the various methods for assessing state policy innovativeness (Walker, 1969; Gray, 1973; Boehmke and Skinner, 2012). Furthermore, they have studied not only the various factors that contribute to state policy diffusion, whereby states adopt policies already implemented by other governments (Grossback et al., 2004; Shipan and Volden, 2006; Gilardi, 2010), but also the considerations that affect a state's penchant for developing and implementing untried policies (Parinandi, 2020). Thus, studies should look into how state propensity toward policy diffusion and innovation may be linked to the development of programs and policies that may improve the employment outcomes of individuals on MOUD treatment and even lessen employment-related racial disparities.

Furthermore, we acknowledge that a more nuanced study of the interaction effects of race and MOUD treatment on employment outcomes within the criminal justice system is beyond the scope of this study. Thus, future work should investigate more fully how referral by the justice system might differentially impact the association between MOUD treatment and employment outcomes for different racial groups. Future work should also look into whether racial disparities in employment outcomes among those utilizing MOUD are heightened or alleviated by various institutional referral sources within the criminal justice system. Finally, we note that this study examines the short-term association between MOUD and employment outcomes. The TEDS data set does not convey information about the long-term association between MOUD and employment. Future studies should look at the long-term effects of MOUD, especially years after clients are no longer in treatment.

5. CRediT authorship contribution statement

BLH conducted the statistical analyses of the data. BLH and DS contributed to the conceptualization of the manuscript, the drafting of the original manuscript, and interpretation of findings. Both authors contributed significantly to all aspects of the study.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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