


Effects of a New York Medicaid Care Management Program on Substance Use Disorder Treatment Services and Medicaid Spending: Implications for Defining the Target Population

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ABSTRACT

AIMS: We examined the effects of a statewide New York (NY) care management (CM) program for substance use disorder (SUD), Managed Addiction Treatment Services (MATS), on SUD treatment services' utilization and spending among patients with a recent history of high Medicaid spending and among those for whom a predictive algorithm indicates a higher probability of outlier spending in the following year.

METHODS: We applied difference-in-difference analyses with propensity score matching using NY Medicaid claims data and a state registry of SUD-treatment episodes from 2006 to 2009. A total of 1263 CM enrollees with high SUD treatment spending (>\$10K) in the prior year and a matched comparison group were included in the analysis. Crisis care utilization for SUD (detoxification and hospitalizations), outpatient SUD treatment, and Medicaid spending were examined over 12 months among both groups. CM effects among predicted high-future-spending patients (HFS) were also analyzed.

RESULTS: CM increased outpatient SUD treatment visits by approximately 10.5 days (95% CI = 0.9, 20.0). CM crisis care and spending outcomes were not statistically different from comparison since both conditions had comparable pre-post declines. Conversely, CM significantly reduced SUD treatment spending by approximately \$955 (95% CI = -1518, -391) and reduced days of detox utilization by about 1.0 days (95% CI = -1.9, -0.1) among HFS.

CONCLUSION: Findings suggest that CM can reduce SUD treatment spending and utilization when targeted at patients with a greater likelihood of high future spending, indicating the potential value of predictive models to select CM patients.

KEYWORDS: Substance-related disorders, program evaluation, multiple chronic conditions, Medicaid, administrative claims healthcare

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Introduction

Substance use disorders (SUDs) are implicated in inefficient healthcare utilization, such as avoidable emergency department visits and hospitalizations.¹ SUDs are chronic conditions that have similar healthcare considerations as other chronic medical conditions.^{2,3} SUDs have no cures, require individual commitment to behavior change, and benefit from long-term engagement with treatment. As with other chronic conditions, there is a subgroup of individuals with SUD who account for a disproportionate share of treatment expenditures. Specifically, a small proportion (~10%) of the SUD population accounts for half of SUD treatment and medical spending.¹ The system of care for individuals with severe SUD is poorly designed to address the needs of this chronically ill population.

In the United States (US), most SUD treatment is provided during short, acute episodes of severe symptom disruption.

Treatment is provided by specialty providers who are often not well integrated with mental health, medical care, or agencies that provide social services.^{4,5} Service fragmentation is especially problematic for Medicaid populations, who have high rates of co-occurring physical and mental health disorders that complicate care and require coordination across multiple providers.¹

To address this issue, state Medicaid programs have been introducing care management (CM) programs to address healthcare fragmentation for patients with chronic health conditions.⁶⁻¹⁴ Prior evaluations of CM programs found that programs have difficulty identifying and enrolling the most appropriate CM clients. These difficulties have led to mixed evaluation findings of program benefits.¹⁵⁻¹⁷ Notably, regression to the mean, where outlier high-spending patients tend to move toward the population average over time, has been



recognized as a phenomenon that undermines the rationale for programs that rely on recent extreme utilization as criteria for enrollment.^{18,19} Among the recommendations from these evaluations is the development of strategies to better identify members who could best benefit from the CM services.²⁰⁻²²

In 2006 the New York Office on Addiction Services and Supports (OASAS) funded a \$25 million CM program entitled “Managed Addiction Treatment Services” (MATS; see reference for detailed program description).¹ The program targeted Medicaid patients whose SUD treatment expenditures generally exceeded \$10 000 to \$15 000 per annum (varied by county), placing them in the top 90th percentile and accounting for approximately half of all state spending for SUD treatment. The program aimed to (1) support engagement in ongoing SUD treatment, (2) provide linkage to physical and mental health care and welfare services, and (3) reduce usage of medically unnecessary high-cost crisis services.²³ In alignment with the chronic care model, the primary objective of the MATS program was the reduction of patients’ use of high-cost detoxification and inpatient services.²⁴

This study has 2 central aims: (1) To examine the 12-month SUD-related outcomes of MATS and (2) to explore whether a predictive algorithm for high future spending (HFS) would have a moderating effect on program outcomes. This post-hoc analysis is consistent with prior CM programs²⁰⁻²² case selection based on statistical models that predict who is likely to have greater needs and have high expenditures in the near future. Specifically, we used a difference-in-difference (DiD) analytical approach with a propensity score matched comparison group to test whether the CM program: (a) decreased crisis care (ie, detoxification, SUD hospitalizations); (b) increased participation in outpatient SUD treatment; and (c) reduced Medicaid expenditures.

Methods

Datasets

We combined data from NY Medicaid claims and a state registry of SUD treatment episodes, Client Data System (CDS), from 2006 to 2009 to create the analytical dataset. Using Medicaid claims, we coded health services utilization and expenditures using procedure and revenue codes. We drew demographic and other clinically relevant patient characteristics from the CDS. All OASAS-licensed providers of SUD treatment in NY enter information on patients’ demographics, current primary substance, recent SUD treatment history, homelessness, and more in CDS. We linked patients in Medicaid to the CDS using a combination of common identifiers and probabilistic matching techniques to account for data entry errors on elements of the identifiers.²⁵ For all Medicaid enrollees with a SUD diagnosis, we were able to link 88% to CDS data. Our linkage rate for HFS patients (ie, SUD treatment spending greater than \$10 000) was 98%, and 99% specifically for patients enrolled in MATS.¹

Participants

Participants (n = 1263) are from 9 of 22 MATS program counties (not including New York City) with local enrollment greater than 80 clients per county. The minimum threshold for the study of 80 participants per county was required to develop stable estimates in regression models adjusting for within county correlation. MATS enrollment occurred over 27 months between October 2006 and December 2008. Individuals were adults aged between 18 and 64 years with SUD diagnosis and eligible to participate in MATS if their past-year SUD treatment expenditures exceeded a threshold that varied by county, ranging between \$10 000 and \$15 000. Program participation was voluntary. MATS enrollees were clinically complex and high users of healthcare services.¹ The counties that participated in the MATS program were diverse in infrastructure, geographic, and demographic factors (eg, population density) as well as resources available at the county level (ie, social and economic factors, social service agencies).

Intervention

The MATS program objective was to increase engagement in SUD treatment, primary care, and other social services with the expectation that these interventions would reduce expenditures by avoiding use of emergency department visits, detoxification, and other inpatient care. While OASAS provided funding and broad guidelines for the MATS program, county governments were given latitude to define specific care manager roles, conduct local program oversight, and create administrative structures to coordinate across local SUD treatment, healthcare, and social service agencies. Initially OASAS provided each county a list of eligible clients culled from queries of Medicaid records for prior year high SUD treatment expenditures. However, this structure for centralized control over eligibility soon proved unwieldy due to complexities in obtaining requisite consents for data sharing and due to lags in information that led to obsolescence in individual contact information. The program structure evolved to one where counties could identify prospective clients and enroll them contingent upon an administrative review by OASAS to verify that recent spending met program criteria.

Each county developed a local program that was responsible for contacting eligible clients, assessing their clinical and social needs, linking them to local services, as well as monitoring client outcomes. According to OASAS program requirements, county programs hired care managers that were responsible for various functions like resource identification, system coordination, advocacy, service monitoring, brokering, and crisis intervention. OASAS operationalized the care manager functions and established minimum performance standards for care managers as follows: each care manager would maintain a minimum of 25 total client contact hours per week; caseloads would include a mix of high,

medium and low activity patients; and, each care manager would maintain an average caseload of 30 patients. Care managers were tasked with reducing barriers to community-based SUD care, which included addressing social, mental health and physical health issues. The services that care managers provided included the identification of health care providers and relevant social service agencies, client referral and scheduling of appointments, provision of transportation for clients to these appointments, home visits, and facilitating follow-up and linkages. The majority (86%) of care managers had a bachelor's degree or higher, most had 3 or more years of prior work experience as a care manager, and over one-third were OASAS-licensed Credentialed Alcoholism and Substance Abuse Counselors (CASACs).

Statistical matching

We used propensity score methods to identify 1263 comparison individuals from a database of 28 500 Medicaid members who were receiving treatment for SUD in the same 9 counties during the same period as MATS enrollment.^{26,27} A matched comparison for each MATS client was drawn in the month of enrollment by selecting the closest propensity score for the specific month among all individuals who never enrolled in the MATS program, in descending order from largest values to ensure best possible matching for extreme values on the propensity score. Matching was conducted without replacement and stratified by gender and county of residence.

To select a match for each MATS participant, we computed monthly propensity scores for the probability of MATS enrollment within each county: $\Pr[y_{it} | D_i, S_{it}, U_{it}]$, where y_{it} is a binary indicator of whether person i enrolled in the MATS program in month t . D_i is a matrix of stable characteristics of a person identified at baseline that includes: gender, education, chronic medical conditions, and significant mental illness. S_{it} is a matrix of variables drawn from the person's most recent SUD treatment admission at month t , including: housing, primary substance use, and criminal justice involvement. U_{it} is a matrix of variables assessing different dimensions of the utilization of medical and SUD services during the 12 months prior to month t , including: frequency of detoxification, emergency department use, inpatient SUD treatment, and Medicaid expenditures. To account for trends in recent service utilization, we also included frequency of detoxification, inpatient, and outpatient SUD treatment in the prior 3 months. To address variation by gender, we included higher-order terms for interactions between gender and inpatient treatment, detoxification, housing status, and primary substance. Finally, we added the square and cube roots of Medicaid expenditures to account for non-linear associations between spending and program enrollment. Analyses were conducted with SAS 9.4 proc logistic (SAS Institute Inc.; Cary, NC).

Measures

Outcomes. We examined the impact of the MATS program on service utilization counts and spending using diagnostic related group (DRG), Healthcare Common Procedure Coding System (HCPCS) codes, and NYS-specific Medicaid billing rate codes. We separately categorized healthcare services into crisis services (eg, emergency department visits, detoxification, hospitalization) and outpatient care.

Covariates. Socio-demographic characteristics for linked individuals were obtained from the CDS, which included a set of binary variables: whether the participant had completed high school or equivalent, homelessness, unemployment, receipt of state assistance, and criminal justice involvement. Participants were coded as currently receiving treatment if they had an open SUD treatment episode in the CDS at the time of enrollment in the MATS program. We also obtained data from the CDS on substance use, including the client's primary substance, frequency of use, and whether the client was a person who injects drugs.

Participants' physical and mental health conditions were identified using Medicaid claims data based on ICD-9-CM (International Classification of Diseases, Ninth Revision) diagnostic codes. Indicator measures were created for serious mental health conditions (ie, schizophrenia, major depression, bipolar disorder, other psychoses) and/or chronic physical conditions (specifically, diagnoses including hepatitis C, HIV/AIDS, chronic obstructive pulmonary disease, asthma, diabetes, cardiovascular conditions). We also calculated the months of Medicaid coverage in the follow-up period.

The probability of HFS was computed for all SUD treatment clients in the 9 counties. The HFS was computed monthly and indicative of the likelihood of SUD treatment spending greater than \$10 000 over the subsequent 12 months. The \$10 000 threshold was used because this was the minimum cutoff OASAS had selected for program eligibility. The variable computation took the form:

$$\text{hfs}_{it} = \Pr\left[\sum_{t+1}^{t+12} \$y_{it} > \$10\,000 | D_i, S_{it}, U_{it}\right],$$

where $\left(\sum_{t+1}^{t+12} \$y_{it} > \$10,000\right)$ is a binary indicator of whether the

sum of SUD treatment spending $\$y_i$ for the person i over subsequent months $t+1$ through $t+12$ are greater than the high-spending threshold (here \$10 000), D_i is a matrix of variables representing individual characteristics at baseline, S_{it} is a matrix of variables drawn from each individual's most recent SUD treatment admission at month t , and U_{it} is a matrix of variables assessing recent utilization of medical, mental health and SUD services during the 12 months prior to month t . We implemented the HFS modeling in SAS 9.4 using proc logistic (SAS Institute Inc.; Cary, NC). The strongest predictors of HFS included homelessness, serious mental illness, HIV/AIDS, and frequent and/or recent utilization of detoxification services.

Analysis

We applied propensity score matching coupled with a DiD approach to compare pre- and post-MATS program enrollment changes in outcome measures between the participants and paired comparison patients. Our approach to propensity score matching ensured that we drew a counterfactual comparison group from the same population as those enrolled in MATS: complex clinical cases with high levels of service utilization and expenditures prior to program entry. The DiD approach allowed us to compare trends in utilization and spending across pre and post-enrollment periods for program participants and their counterfactual comparisons. We examined the impact of the MATS program on days of utilization of SUD care (detoxification, SUD hospitalizations, and SUD outpatient services) as well as Medicaid SUD expenditures. These Medicaid expenditures did not include spending for the MATS program since these were separately funded through contracts to the counties. Then we examined the impact of the MATS program on outcomes moderated by an individual's probability of HFS for SUD treatment by entering an interaction term into each model. The latter analysis examined the benefit of MATS for those who would be selected based on a predictive algorithm for HFS.

The distribution of healthcare utilization days across domains was characterized by a large proportion of zero values (no utilization of a particular type) and over-dispersed counts of days. We found that zero-inflated negative binomial (ZINB) models had the best fit as indicated by the Akaike information criterion (AIC) and Bayesian information criterion (BIC).²⁸ To appropriately analyze the healthcare payment data, which were characterized by non-normal distributions with heavy tails, we first trimmed values to the 99th percentile (to not give undue influence to extreme outliers) and then used Generalized Gamma Models (GGM).^{29,30} The GGM was modeled using the STATA "streg" command with clustering by county.²⁹

Each model was adjusted by demographic characteristics (ie, age, gender), a binary indicator of less than high school education, any serious mental health condition (ie, major depression, bipolar disorder, schizophrenia, and other psychoses), chronic health conditions (ie, hepatitis C, HIV/AIDS, chronic obstructive pulmonary disease, asthma, diabetes, cardiovascular conditions), number of days of Medicaid coverage at follow-up, and baseline value (over 12 months prior to enrollment date) of the outcome measure. Subsequent analyses to examine effect moderation by the probability of HFS included the HFS risk score and interaction between HFS and indicator of enrollment in the MATS program. For ease of interpretation, marginal effects for treatment outcomes after adjustment for covariates set at sample means were computed. All modeling accounted for the clustering of observations within counties and was conducted using STATA (StataCorp LLC; College Station, TX).³¹

Results

Table 1 presents descriptive data at baseline for the MATS participants and the statistically matched comparison group. MATS participants (and matched controls) were on average 40 to 41 years old, predominantly male, and alcohol was the most common primary substance related to SUD treatment. The MATS group had high prevalence of homelessness, criminal justice involvement, and acute healthcare services use. Additionally, there was high prevalence of significant mental health and other chronic medical conditions. The middle column between the study groups presents measures of effect size (Cohen's d for continuous variables, odds ratios for proportions) as an indicator of the magnitude of the differences. Cohen's d values $\geq |0.20|$ and odds ratio values below 0.67 (for odds ratios <1.0) and greater than 1.50 represent clinically substantive differences between groups.^{32,33} We display effect size measures because the large sample size would lead to test results showing statistically significant, but clinically meaningless differences. The comparison group derived from the propensity score methods was statistically well matched with the MATS participants across all the study variables.

Care management program outcomes

Table 2 presents outcomes for the MATS program compared to the propensity score matched group. We present marginal effects (ie, regression adjusted predicted values for group differences on the outcomes) for all participants enrolled in MATS. There were no statistically significant differences between MATS participants and comparison individuals on service utilization for emergency department visits or hospitalizations. The groups differed significantly in their utilization of outpatient SUD care, with the MATS participants having notably more outpatient treatment visits than comparisons during the 12-month follow-up. There were no statistical differences in SUD specific or total Medicaid expenditures for healthcare.

Outcomes among HFS patients

The right column of Table 2 shows the marginal effects for individuals predicted to be HFS. Descriptive data at baseline for this group can be found in the Supplemental Table 1 and the statistical difference between this group and the overall population of SUD treatment was previously reported in the baseline study.¹ Specifically, the MATS program led to approximately one less day of detoxification among patients predicted to have high future SUD treatment spending. Additionally, the MATS was associated with a statistically significant reduction in SUD treatment expenditures of approximately \$955 over the follow-up period among the HFS. Yet, there were no statistical differences in total Medicaid spending among those predicted to be HFS for SUD related services. Figure 1 plots the relationship between prediction scores and SUD Medicaid spending. The figure shows that at a probability level of

Table 1. Characteristics of Care Management (Intervention) and Comparison Groups.

VARIABLES	COMPARISON (N = 1263)	EFFECT SIZE	CARE MANAGEMENT (N = 1263)
Demographics			
Less than high school	32.3%	1.0 [†]	32.3%
Age, mean (SD)	40.0 (9.0)	0.05 [*]	40.5 (9.4)
Black	38.6%	0.99 [†]	38.3%
Male	58.7%	1.00 [†]	58.7%
Homeless	16.3%	1.03 [†]	16.7%
Medicaid eligibility months, mean (SD)	8.7 (4.2)		9.3 (3.6)
Arrested in the last 6 months	18.1%	1.01 [†]	18.3%
Primary substance is alcohol	42.6%	1.03 [†]	43.9%
Health services utilization			
Emergency department utilization	59.3%	0.94 [†]	57.9%
Rehab admissions, mean (SD)	1.5 (1.3)	-0.04 [*]	1.5 (1.3)
Detox admissions, mean (SD)	1.4 (2.5)	-0.02 [*]	1.3 (2.1)
Outpatient visits, mean (SD)	79.3 (78.4)	0.02 [*]	80.9 (80.9)
Currently in SUD treatment	55.8%	0.97 [†]	55.0%
Medicaid spending (US dollars)			
Total Medicaid, mean (SD)	25930 (24773)	-0.07 [*]	24235 (21795)
SUD treatment, mean (SD)	12442 (13470)	0.04 [*]	12898 (11042)
Clinical complexities			
Severe mental health	65.0%	1.03 [†]	65.6%
Chronic disease	42.8%	0.96 [†]	41.8%
Hepatitis C	25.6%	0.94 [†]	24.4%
HIV/AIDS	5.1%	0.95 [†]	4.9%

The table describes baseline characteristics of individuals enrolled in the Care Management program and the statistically matched comparison group. The central column shows measures of effect size to indicate magnitude of differences between this 2 conditions. Cohen's *d* indicates size differences for continuous measures while odds ratios indicate differences for proportions.

*Cohen's *d*.

[†]Odds ratios.

approximately .50 for high future expenditures, the MATS program crosses a threshold that would have statistically significant savings. The figure also shows that higher prediction scores for HFS were associated with greater reductions in SUD treatment expenditures for MATS clients.

Discussion

The present study examined whether offering a CM program to high-needs/high-expenditure SUD treatment patients reduced SUD-related crisis care and spending to Medicaid. The MATS program was successful in recruiting individuals with high Medicaid spending and social needs.¹ MATS program participants had a higher engagement in SUD outpatient treatment than statistically matched controls, something that

was consistent with the program objectives and consistent with a chronic care model approach to SUD.^{13,34,35} Yet, the MATS program did not reduce SUD-related detoxifications, hospitalizations, or spending in comparison to a statistically matched group. These findings suggest that increased outpatient care will not necessarily lead to reduced crisis care or expenditures. Conversely, the MATS program was effective in reducing detoxification days and SUD treatment spending among those for whom a predictive algorithm indicated an increased likelihood of future high SUD treatment expenditures. These findings are consistent with a recent study in a Medicaid population that used predictive algorithms to better target CM services to improve quality of care for individuals with a higher likelihood of poor future outcomes.¹²

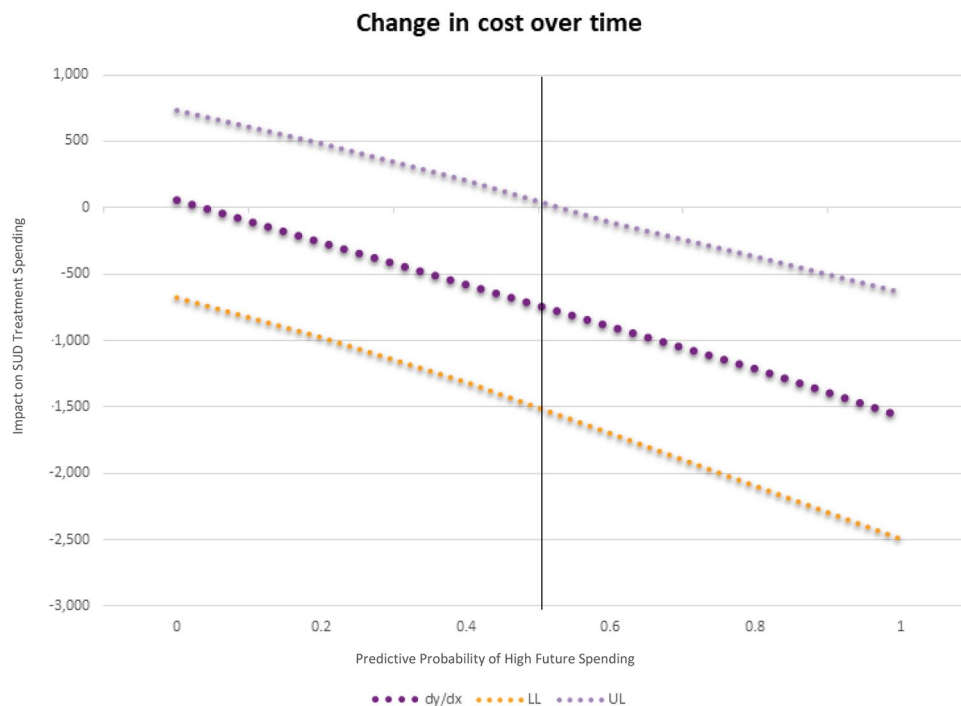
Table 2. Adjusted model outcomes for Care Management (Intervention) group and for Care Management group with high future spending.

	MARGINAL EFFECT OF CM (95% CONFIDENCE INTERVAL)	MARGINAL EFFECT OF CM FOR HFS (95% CONFIDENCE INTERVAL)
SUD services utilization		
Detox admissions	-0.75 (-1.71, 0.21)	-0.99 (-1.92, -0.05)*
SUD hospitalizations	0.05 (-1.94, 2.04)	-0.71 (-3.05, 1.64)
SUD outpatient days	10.47 (0.90, 20.03)*	10.80 (1.29, 20.32)*
Medicaid spending (US dollars)		
Total Medicaid	\$818 (-1004, 2645)	\$-827 (-3576, 1922)
SUD Medicaid	\$-101 (-783, 551)	\$-955 (-1518, -391)*

Abbreviations: CM, care management; HFS, high future spending; SUD, substance use disorder.

The table presents marginal effect differences for the care management program in comparison to the statistically matched group.

*Significant at $P < .05$.

**Figure 1.** Medicaid spending for SUD treatment.

Abbreviations: LL, lower level of 95% confidence interval; UL, upper level of 95% confidence interval.

The figure shows the relationship between the HFS prediction score and the marginal effect on total SUD treatment spending for the CM program. While the 95% confidence interval (ie, the region bounded by the top and bottom dotted lines) indicate that the marginal effects are not statistically significant across the full range of prediction scores, there is a notable downward slope, with the confidence interval crossing the null at a prediction score of approximately 0.50, indicated within the figure by a vertical line. The trend suggests that there is some effect for CM on total SUD spending that could be significant in larger sample sizes or with greater precision in measuring risk of HFS.

The lack of effect on crisis care and expenditures for the MATS program as implemented was notable given that the enrollees were high needs, high spending, and had large reductions in expenditures and crisis utilization from the year prior to the program. The lack of effect was evident only when compared to statistically similar individuals who did not receive CM. Notably, the analysis of expenditures did not account for the costs of the MATS program, so there were no savings to offset the investment in the program.

The program design was founded on the premise that high-expenditure clients have diverse and complex medical and psychosocial needs that require care that is coordinated across varied health and social services providers. There may be multiple reasons for a lack of effect. One is that it is possible that the latitude given to county governments to implement the program according to local exigencies and preferences created variation in execution that attenuated overall program effects. We conducted analyses of county variation (results not

presented here), but there were no strong indications of county programs that had substantially better outcomes than others. Another reason is that the focus on selecting clients based on a recent history of high expenditures for SUD treatment caused difficulties in program implementation that affected enrollment. Eventually, the county programs created new strategies for recruiting clients that presumptively met the criteria. Although the local recruitment was subject to program eligibility verification by the state agency, this “bottom-up” outreach process may have added bias to the evaluation. The material effect of this was that many of these identified clients were recruited because they were already engaging in systems of care (eg, hospitalized for SUD treatment).

On the face of it, the reductions in expenditures for the MATS participants and comparison groups appear to be consistent with a regression toward the mean effect, where the average for a group of outliers on a distribution is more likely to move closer to the center of the distribution at subsequent observations.³⁶ In a related vein, there are clinical observations from the field as well as from the data presented here that may help explain the large reductions in utilization and expenditures. Specifically, a close examination of baseline characteristics of the MATS group suggests that those enrolled in the program were largely engaged with treatment and/or social safety net services at the time they were enrolled.¹ That is, clients that were enrolled were already proactively engaging systems of care yet there may have been more disenfranchised clients for whom the model may have been a better fit.

The foregoing suggests that one of the reasons for non-significant effects of the MATS program was the recruitment of individuals who were already addressing their acute care needs. That is, these individuals were either benefiting from engagement with medical or other services or had passed through a period of crisis and were stabilizing. On the other hand, the program may have had larger effects on a group that was entering a period of high healthcare needs. To examine this proposition, we explored whether the use of a predictive model for high future spending could lead to a more effective and efficient recruitment strategy. The predictive model found that those who were to become HFS individuals were slightly younger, more socially disenfranchised (eg, greater homelessness), less costly to Medicaid at baseline, and less engaged in outpatient care than most SUD clients. Because they were somewhat disconnected from systems of care, these HFS individuals were not readily accessible to the MATS programs. As mentioned previously, most MATS clients were already in some form of treatment when enrolled. Yet, the benefits of MATS were most apparent among those who were not already connected to the treatment system and/or social safety net. Evidently, future CM implementation, as well as research, will need to focus on strategies to better locate and engage those who are most disconnected. Our findings thus substantiate prior evaluations of CM programs that found it difficult to

identify and enroll the most appropriate CM clients.¹⁵⁻¹⁷ Taken together, these findings highlight the need for development of strategies to better identify members who could best benefit from the CM services.²⁰⁻²²

One important component of the chronic care model is ensuring ongoing monitoring and engagement in care.¹⁴ Consequently, the CM program design focused on helping patients become engaged in SUD treatment as well as providing assistance in linkages to social welfare, medical, and psychiatric services. The results here suggest that the CM program was successful in getting these individuals to attend outpatient care, with an average increase of 10 visits per year compared to statistically matched controls. While this increase in engagement was consistent with the program model, it unexpectedly was not associated with reduced utilization or expenditures since both the MATS and statistically matched groups had similar decreases in crisis utilization and spending. On the other hand, due to limited power, the analysis cannot address the question of whether a greater level of outpatient engagement contributed to lower utilization among those at the highest risk of a future crisis and spending. It may well be that the benefits of CM for this latter group are partially mediated by outpatient engagement.

This study represents the first evaluation of a statewide CM program for SUD and has implications for ongoing healthcare reform in the United States.³⁷ Notably, many of the newly enrolled under Medicaid expansion have SUD and require better coordination between primary and specialty care.^{4,38,39} NYS has long covered treatment for SUD among non-elderly, childless adults through Medicaid. Additionally, New York is large with significant population and geographical diversity (eg, urban/rural). Consequently, lessons learned through this CM program presage challenges that other states will face.

The results of this study should be viewed considering its limitations. The first is that the nature of the government-run program precluded randomizing patients into control and intervention groups. The MATS programs worked hard at finding and enrolling eligible patients, and consequently, could not justify withholding services. In response, we devised a complex quasi-experimental design that matched patients at the time of enrollment, county of residence, and many individual characteristics derived from large databases. While the comparison group is very similar to those enrolled in MATS, there may be some unobserved factors that are not controlled in the analyses. Particularly, the study does show the analytical value of methods that match on observed characteristics to distill program effects from other naturally occurring phenomena. One question may arise, drawing from recent work by Daw and Hatfield,⁴⁰ about whether our comparison group was subject to mean reversion because we may have sampled from a population different than CM enrollees. If so, the comparison group could have been outliers within their (different) population. We contend, however, that the appropriate population

for sampling were individuals who had high utilization and expenditures at baseline since that was the criteria for program eligibility. Because of data constraints, we were not able to test for the parallel trends assumption but note that Ryan et al⁴¹ found that DiD with propensity score matching methods provided less biased effect estimates when there are some differences in trends at baseline than DiD without matching. We account for baseline trends in our matching protocol by including measures for both 12 months and most recent 3 months encounters. Another limitation is that model variables were drawn from administrative data, which have imprecision as well as a limited assessment of clinically relevant factors affecting the population.⁴² This imprecision can cause statistical noise in the analysis that is partially mitigated by the study's large sample size. The analyses derived from administrative data cannot address outcomes specific to the personal experiences of individuals (eg, substance use behavior) that are not reported in these databases as they would be in studies where there were research interviews. In terms of the generalizability of findings, it should be noted that the MATS program targeted patients with high SUD expenditures, rather than more broadly on those with high overall Medicaid spending. Patients with high SUD treatment spending may be different from SUD patients with overall high Medicaid expenditures such that they may have different patterns of use of healthcare services. Future research should examine how patients with high SUD-only Medicaid spending differ from those with high overall Medicaid expenditures in terms of outcomes from CM programs. We note that the reported effect of MATS among those with risk of HFS needs to be interpreted with caution until future studies can demonstrate similar findings. Finally, we note that the form of the MATS intervention presented here was implemented in the late 2000s. The findings of this study may not reflect on the current versions of MATS or care management programs for this type of population.

Conclusions and Recommendations

In summary, we did not find that the MATS program reduced crisis care utilization or Medicaid expenditures among a clinically complex and recently costly group of individuals with SUD. The lack of effect may be due to several factors, especially regression to the mean. Analyses suggest that the MATS program was indeed effective in reducing utilization and spending among those who were at imminent risk of expensive care utilization. The findings speak to the importance of carefully defining the targeted population for CM. CM will more likely lead to reduced expenditures among those who are entering a period of risk for high spending, not necessarily those who have just passed through such a period and are becoming more stable. While the analyses presented here give a limited indication of what factors are important in assessing future risk, the general picture is that those who have had recent crisis care coupled with low social capital, high-severity substance

dependence, and little history of outpatient SUD engagement are most likely to benefit from CM.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Charles J Neighbors, Rajeev Yerneni, Yi Sun, and Constance Burke. The first draft of the manuscript was written by Charles Neighbors, Sugy Choi, Megan A O'Grady, and Rebecca McDonald and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.


Ethical Approval

Approval was obtained from the ethics committee of the National Center on Addiction and Substance Abuse, Columbia University (#168). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Data and/or Code Availability

The data that support the findings of this study are available from New York State Department of Health but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the New York State Department of Health.

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Supplemental Material

Supplemental material for this article is available online.

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