Transit and Treatment: Aligning Systems to Address Substance Use in Connecticut

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Abstract

Objective: Determining whether aligning transportation with substance use and mental health treatment lowers costs and improves equity, possibly from better access, retention, and fewer missed/late appointments. **Data Sources and Study Setting:** Substance use treatment providers/programs in Connecticut (CT), near a new (2015 opening) bus rapid transit line with 10 stations. Providers' annual expenditures are from federal tax forms (2013-2018). Annual program-level client counts, treatment-type and location data, for 50 providers, are from CT Department of Mental Health and Addiction Services (DMHAS), resulting in 1,534 observations. **Study Design:** We estimate cost efficiency models with quasi-experimental, multivariate regressions. Our hypotheses are that unit operating costs fall when providers have programs within ½ mile from new transit stops, after versus before the opening; and providers treating both mental health and addiction patients within ½ mile from new transit stops, after versus before the opening, face lower total operating costs. We convene monthly stakeholder panel discussions, with 5 local treatment providers; state-level Department of Public Health, DMHAS, and CT Department of Transportation (DOT); and Capitol Region Council of Governments. Stakeholders discuss quantitative model development and alignment strategies. **Data Collection/Extraction methods:** We merge annual provider-level operating expenditures, from publicly available IRS forms, with station locations and DMHAS program/provider-level secondary data (locations, client counts/dates, treatment types, demographics). **Principal Findings:** Unit costs decrease with additional patients treated, for providers with programs near new transit stations; and providers treating multiple disorders close to new transit face lower operating costs. Community stakeholders share past strategies addressing transportation barriers (vouchers, medical transportation, ride-shares, and van purchase). New alignment strategies include purchasing a building near a transit station; and a new DMHAS/DOT collaboration placing social workers at transit stations. **Conclusions:** Aligning systems - transit with substance use treatment and health promotion/prevention programs - can lower costs and enhance equitable access.

Keywords:

- **Substance Abuse: Alcohol/Chemical Dependency/Tobacco**
- **Health Equity**
- **Integrated Delivery Systems**
- **Health Care Costs**

Callout Box:

- Substance use treatment in the U.S. is costly. Transportation is often a barrier to substance use treatment, leading to inequities among those without easy access to transportation for reaching treatment.
- Missed and late appointments because of lack of reliable client transportation can increase operating costs for providers.
- We first study how substance use treatment provider proximity to a new transit line in central Connecticut has impacted provider operating costs, using a quasi-experimental regression framework.
- After uncovering evidence that transit proximity lowers costs, we shared the results with an advisory panel of local stakeholders, which began meeting monthly starting in May, 2020.
- The advisory panel coalesced to develop an NIH grant proposal for community engaged scholarship, which will bring substance use and mental health treatment as well as homeless services to several transit stations in Connecticut.

Introduction

Illicit substance use and prescription misuse cost our economy more than $600 billion each year.[1] Indirect costs, such as lost productivity and crime, are higher. Funding of substance use disorders (SUD) treatment is an important aspect of these costs. For instance, it costs approximately $4,700 per year on average for a typical patient to receive methadone treatment.[1] With roughly 2.7 million people 12+ years of age receiving treatment in 2020 at a SUD-specialty treatment facility annually,[2] policy makers and taxpayers must consider SUD treatment costs through a lens of reducing inefficiencies.

Increasing access and retention in treatment services is a critical step in this process of increasing the cost efficiency of the treatment system. Transportation barriers are a consistently raised barrier to successful treatment completion[3–6] and a driver of inequity.[7–9] While expanding transit can be beneficial, these social services are costly, and their added value should be considered. This paper examines the impacts of transit systems on substance use disorder treatment, and what these impacts imply for system alignment. In particular, strong transportation systems can impact substance abuse treatment provider operating costs. Proximity to transit can raise treatment facilities' patient volumes (and/or reduce unbillable clinician time due to missed appointments) which may push down their unit cost curves (i.e., economies of scale). Nevertheless, health services more closely aligned with transit may adequately, cost efficiently, and equitably serve this substance abuse treatment population, and enhance public health by alleviating the opioid crisis and achieving cost savings.

Few studies have examined economies of scale for substance abuse treatment.[10–13] Duffy et al.[12] base their analysis on a first order logarithmic cost function for a cross section of U.S. outpatient treatment facilities in 1997. They find statistically significant evidence of scale economies for outpatient admissions. They also note how demographic variables are often the best available indicators of "case-mix". Beaston-Blaakman et al.[10] estimate an average cost function. They use "point prevalence" (the count of active clients on a specific day of the year) as a proxy for size (rather than actual client counts) and find evidence of scale economies. Dunlap et al.[13] estimate two total cost functions for methadone treatment, one based on patient "average daily census", and the other based on "primary services" at methadone treatment programs and find some evidence of scale economies. Cohen and Morrison Paul[11] find economies of scale at hospitals providing outpatient treatment in WA. But none of this previous research uses an identification strategy that overcomes endogeneity of outcomes and/or other variables.

Connecticut (CT) recently introduced a massive transit initiative spanning 4 municipalities. The introduction of this new transit system provides an opportunity to use a quasi-experimental, generalized difference-in-differences empirical estimation approach enabling us to assess the impact of alignment of transit and substance use treatment. Our quasi-difference-in-differences approach (as in Autor[14]) enables us to overcome the endogeneity of outcomes and other variables.

Many providers also offer mental health services, so cost savings of treating both substance abuse and mental health issues in one facility (economies of scope) are possible. How enhanced transit impacts costs via economies of scale/scope will have implications for coordination of systems across medical, public health and social services.

Another aspect involves more qualitative, community-engaged scholarship that is intended to discover what providers and state agencies are currently doing to align systems, and what barriers might impede support for their further alignment to achieve the objective of cost savings and greater equity through better access, retention and fewer missed/late appointments.

Methods

The scientific approach consists of an identification strategy that relies on a set of quasi experiments. These experiments include a Generalized Difference-in-Differences (G-diff-in-diff) approach (as in Autor[14]) and a Cost Function Analysis (CFA). CFA is a technique from the Industrial Organization literature in economics, focusing on the production process. CFA has been applied to many different industry studies (such as hospitals and manufacturing) to aid in decisions of how many firms, how much of each input each firm should use, and what size firms to have in a given industry. While some studies (e.g. Cohen and Morrison Paul[11]) have considered substance abuse provider costs using CFA, and other studies (such as Morrison and Schwartz[15] and Cohen and Morrison Paul[16]) have examined transportation infrastructure in a CFA framework, no known work has considered a systems approach of including social services and medical services in the CFA with a proper identification strategy. CFA can help with decisions about whether it is more efficient for many small firms to produce small amounts, or fewer large firms to produce large amounts, of a product or service in an industry. CFA has also been widely used to understand if it is less costly for production of two or more distinct products or services to each occur separately in different firms, or together in one firm (i.e., mental health and substance use disorder treatment). Underlying cost functions is the production process, where "inputs" are converted to "outputs".

Substance use treatment is costly, and minimizing costs while providing effective treatment is a challenge. A crucial point about CFA is that it helps determine how much of a product firms should make, and how the firms should produce the products, in order to operate "cost efficiently" (that is, to minimize the average costs of producing the product). When substance abuse clinics are not using the right input mix, financial resources are wasted, and some people may not get the care they need. In practical terms, this inefficiency might reflect unbillable time and/or underutilized space. Also, integrated care models, which treat mental health and substance abuse concurrently are effective[17] but are rarely available in community clinics.[18] While it may seem to be a trivial problem to solve, it is complex since there are many other variables affecting a firm's decision of how to produce its product(s). It is necessary to control for these factors with regression analysis with CFA. CFA assumes a firm's manager chooses the combination of inputs (including labor and capital) to minimize production costs, given a desired level of output. Regression analysis estimates the parameters of a cost function model and test hypotheses. The generalized Leontief (GL) cost function was used by Li and Rosenman[19] and Cohen and Morrison Paul[11] for hospital costs, and Morrison and Schwartz[15] and Cohen and Morrison Paul[16] for public infrastructure impacts on manufacturing. One can add time fixed effects interacted with dummy variables for near versus far from new transit service. The G-diff-in-diff GL cost function is:

$$(1)\ \ln(OpCost_{it}) = \beta_0 + \beta_1 \ln(NClients_{it}) + \beta_3 \ln(NClients_{it}) \times Distance_i$$
$$+\beta_4 \ln(NClients_{it}) \times Year_i + \beta_5 \ln(NClients_{it}) \times Distance_i \times Year_i + \beta_6 Z + \epsilon_{it}$$

In the context of research on substance abuse treatment providers and social services, $OpCost_{it}$ is provider i total costs in year t; $NClients_{it}$ is the service produced, or "output", which here represents the number of clients treated by provider i in year t. Z represents a vector of control variables, including the case-mix variables that measure characteristics of clients which may lead to different costs; an urban/rural dummy; and possibly others. Importantly for this study, $Distance_i$ is a vector of indicators for proximity to transit (or increased transit service); $Year_i$ is a dummy variable that equals 1 if observation i is after the opening of the transit line (i.e., post-2015), and 0 otherwise; and $Distance_i \times Year_i$ are interaction terms for the year indicator with the proximity dummy; and ϵ_{it} is a random error. The "treatment effect" is the regression coefficient estimate, β_5 , which if statistically significant, indicates how treating more clients impacts operating costs for providers in close proximity to transit after the transit opening. Such a treatment effect approach is a novel identification strategy to determine the causal effects of client volume on provider operating costs.

One way to assess potential implications of system alignment on cost efficiency in the current context is with economies of scale. When a clinic rents space that is not used to full capacity due to inability to recruit/retain staff, the average costs of treating patients are higher than when the facility is fully staffed and filled to capacity. An example is a densely populated area where large numbers of individuals need treatment. Providers might treat clients at a lower cost per patient by expanding their facilities so that they can spread out the fixed costs of a larger facility over greater patient numbers. With a larger facility in a city, costs per patient may be lower when more patients are treated because there is a steady flow of potential clients. So, renting a larger facility may lead to a lower cost per patient ("economies of scale"). Opportunities for system alignment with transit may exist to yield similarly lowered costs. In inaccessible areas, clinics may end up with unused capacity if they expand because of the lighter flow of clients, resulting in higher costs per patient (diseconomies of scale). But transit may enable more people to access treatment who otherwise would not. The CFA can allow for separate economies of scale hypothesis tests for each clinic.

Using regression analysis for a sample of clinics is one approach to assess how the scale of operation impacts firms' average costs, while controlling for other variables that may affect costs. Average costs (AC) are defined as operating costs divided by output ($OpCost_{it}/NClients_{it}$). Marginal costs (MC) are the change in total costs resulting from a change in output ($\partial OpCost_{it}/\partial NClients_{it}$). In general, microeconomic theory indicates firms' AC curves are U-shaped, and the MC curve is upward sloping and intersects the AC curve at the bottom of the U. The cost function can be used to compute the ratio of MC over AC. This ratio, MC/AC, is obtained by differentiating the cost function (1), and plugging in the parameters (β's) that are estimated from regression analysis: MC/AC = [($\partial OpCost_{it}/\partial NClients_{it}$)]•[$NClients_{it}/OpCost_{it}$]. If MC/AC <1 (>1), economies (diseconomies) of scale are present; that is, AC>MC (<MC) and AC is decreasing (increasing) when the clinic produces more of its product.

This pattern implies that if clinics expand the amount of product they generate, all units of the product can be generated more (less) cheaply, on average; the firm is on the downward (upward) sloping portion of its AC curve, so producing more (less) product moves the clinic lower on its AC curve closer to the minimum. Elasticities of scale are obtained by taking derivatives of (1) with respect to each Y variable and summing the derivatives.

The elasticity of scale is $\varepsilon_{TC,Y} \equiv$ % change in $OpCost_{it}$ for each % change in $NClients_{it}$, which is equal to: [$\partial OpCost/\partial\, NClients$]•[$NClients\,/\,OpCost$]. If the regression coefficient β_5 in equation (1) above is statistically significant, the economies of scale estimates are impacted by proximity to transit, and therefore future system alignment could further enhance cost efficiency.

Similarly, when considering both mental health and substance use treatment, the elasticities of scope/specialization are given as:

(2) $\varepsilon_{MCm,Yl} \equiv [\partial^2 OpCost/\partial NClients_m\, \partial NClients_l] \bullet [NClients_l/MC_m]$,

where (l, m) stands for number of mental health clients and number of substance abuse clients.

After estimating each regression model, parameter estimates are plugged into (1) and the mean values of all the explanatory variables' data for each provider, across all years, are used to compute elasticities. The t-statistics for the elasticities are obtained by a method (Cohen and Morrison Paul, 2004)[11] to evaluate each clinic's elasticity at the mean of all of years of data.

The substance use treatment literature (e.g., Stein et al.[20] and Wu et al.[21]) has indicated that treatment access across different demographic groups is an equity issue. One reason for few substance use treatment CFA studies is the lack of sufficient publicly available annual provider-level client count data and demographics. To address this issue, collaborative data agreements were formed with state agencies in CT. The data coverage is for 2013-2021, at the provider level. These data include client counts (admissions and/or discharges), overall client demographics, primary treatment (alcohol or drug use or both), and completions. Duffy et al.[12] explain the importance of controlling for client mix. Others, such as Yeom and Shepard[22] note that gender differences can have impacts on costs. So, client mix variables were included as "shift" variables in the cost function. The set of case-mix related variables include the percent of provider's clients who are Black, who are Hispanic, who are female, who are in age groups 18-25, in age groups 26-34, and in age groups 35-44, however we find that these variables are highly colinear with the provider-level fixed effects. These provider-level fixed effects (which can also represent variation in client mix) enabled us to consider how and whether access among different client demographic groups is different, and in turn, if system alignment would be synergistic with enhanced equity. This study was determined to not meet the criteria for human subjects research due to the use of publicly available datasets and provider-level data.

Data

Cost data (measured as annual total operating costs) at the provider-level were obtained from publicly available IRS 990 forms for nonprofit organizations, and the cost data were merged with client count and treatment type data at the provider level, which was obtained from CT DMHAS from years 2013-2018. The IRS 990 forms were obtained for annually for all providers. CT DMHAS data includes client counts. These IRS records for providers contain annual detailed information on total wages and salaries paid; total number of employees; rental capital prices; value of owned physical capital (buildings and equipment); and total operating costs. Due to provider and program openings and closings during the time period, the data is an unbalanced time series which includes 50 providers across 6 years resulting in 262 provider-years and 1,534 program-years.

Results

Table 1 provides summary statistics for key variables. We plotted the locations of programs, providers, and CTfastrak stations in Figure 1. The greatest concentration of programs is in the Hartford area, which is also a large population center and the state capital. The green dots are the CTfastrak locations. The blue and red dots are program locations. The red dots are program locations within ½ mile of a CTfastrak station location. 5.8% of programs are within a quarter-mile of a new station, 6.1% within a half-mile, 17.0% within one mile, and 21.4% within two miles.

Economies of Scale

We first report estimates of economies of scale. Our current preferred model has operating cost as the output variable and total volume of clients as an independent variable. The elasticity of the dependent variable to the volume variable in each regression is given by the coefficient on the triple difference variable. Our models consider programs within ½ mile of new stations (see appendix for estimates varying this distance).

Elasticity compares a percentage change of cost and volume. An important outcome of interest is not only if a client attends a program, but if the client completes the treatment program. Table 2 presents two versions of our main result: cost-volume elasticity and cost-percent completed semi-elasticity. Elasticity of costs with respect to client count, in column 1, is estimated using a log-log model. Semi-elasticity (in column 2) is estimated using a model where the output/dependent variable, cost, is logged, while the health outcome, % of patients completing treatment, is not logged. In part, this is because the variable, % of patients, includes zeros which cannot be logged, and also it is already in a percentage form. In both cases, the coefficient is negative, representing a decrease in elasticity as volume increases. This means that the cost per client and the cost per client completing treatment goes down as volumes increase, as a result of new transit stations opening within ½ mile of treatment providers.

Economies of Scope

To estimate economies of scope, we create two scope variables, a scope percentage and a scope indicator. The scope percentage gives for each program the percentage of clients who received two or more services. 82% of programs had zero clients who received two or more services (that is, 82% of programs had all of their clients only receiving one service). Before the new transit stations were installed, only 41 programs saw clients receiving multiple services. After the transit installation, this increased to 47 programs. However, more than 75% of programs who had clients receiving more than one service had a majority of clients receiving multiple services. The scope indicator variable is equal to 0 if the program saw only clients receiving one service before the transit installation and 1 if the program saw some clients receiving more than one service after the transit installation.

In Table 3, we estimate a model with a triple difference of the scope variable (one of the independent variables) against log of total cost (dependent variable). The continuous scope variable is not logged, as it is in a percentage form (between 0 and 1). The negative coefficient on the continuous scope semi elasticity tells us that when the new station increases the proportion of nearby programs (within ½ mile of a new transit station) who see clients for multiple services, the cost per client declines. The binary scope variables are not logged as it is on a 0-1 scale. The negative coefficient on the binary scope semi elasticity considers what happens to programs who before the new stations did not have any clients who received two or more services but began to have clients who received multiple services after the new line was running. For this situation, there is also evidence of reduced cost elasticity resulting from the transition. There are also control variables in these economies of scope regressions, including set of case-mix related variables include the percent of provider's clients who are Black, who are Hispanic, who are female, who are in age groups 18-25, in age groups 26-34, and in age groups 35-44.

System Alignment

After generating empirical evidence that transit proximity reduces costs, as described above, a major objective has been to implement system alignment between the transportation, public health, and substance use treatment sectors. At the start of the 44-month project, an advisory panel, that met monthly, consisting of representatives from state agencies, community providers, other nonprofits, and university faculty/researchers, was formed. Each representative presented an overview of their services and programs. Over time, the panel evolved into a cohesive group in support of greater coordination among systems through alignment. The panel agenda has focused on considerations of funding sources for implementation of treatment and transit system alignment strategies in the Connecticut area.

At the start of the advisory panel meetings, the focus was on "ice breakers" so that members from various agencies and organizations would become more comfortable sharing experiences with each other. The initial ideas for system alignment included encouraging providers to open sites near transit; and changing transit departure/arrival times to coincide with the appointment times at providers. While the group quickly realized these ideas could be challenging to implement, they also noted that alignment of financial incentives could encourage some forms of systems alignment. This was particularly relevant to the providers on the advisory panel, with the empirical research findings of operating cost reductions from new transit nearby.

As the advisory panel discussions on transit programs progressed, the most utilized transit services were identified. The largest transit program is the CT Department of Social Services Medicaid Non-Emergency Medical Care Transportation (NEMT) program. The CT DSS web site[23] describes NEMT as follows: [NEMT] "is an important benefit for Medicaid members who need to get to and from Medicaid-covered medical services but have no means of transportation." In an April 12, 2019 update to the Medical Assistance Program Oversight Council on NEMT it was noted that NEMT is "an inherently challenging service to provide" and "there is no magic wand here in Connecticut – or in any state – that can make a perfect program".

The Department of Social Services' contract for services is provided by Veyo, a "Total Transit Company." Veyo coordinates multiple modes of transportation. Bus passes may be provided if the member lives near a bus stop and is physically able to ride a bus. Mileage reimbursement may be eligible based upon the total miles driven to the member's appointment. In cases when the member is not able to ride a bus or get driven to their appointment, Veyo will schedule a ride based upon the individual's transportation needs. Veyo requires a medical necessity form to be completed by a healthcare provider explaining why the member is unable to take public transit. Based upon review of statewide Veyo utilization report data from June 2022 to December 2022 the seven-month of total all member completed trips was 982,479 for a seven-month average of 140,353 completed trips. The total number of completed statewide trips by reason of drug utilization during the seven-month reporting period listed was 397,095 for a seven-month average of 40.42 percent. These drug rehabilitation figures are one of twenty-four reasons for completed trips offered by Veyo services.

Second is the CT Department of Mental Health and Addition Services (DMHAS) transportation through the Substance Use Access Line. The CT DMHAS web site[24] describes Access Line as follows: "The 24/7 Access Line, operated by Wheeler and funded by Connecticut's DMHAS, facilitates access to substance use services for Connecticut residents. Wheeler Staff use a recovery-oriented approach to ask screening questions, and provide callers with education, support, hope and tangible assistance to individuals having difficulty living with substance use issues. Coordination of DMHAS-funded transportation to and from inpatient/residential programs, if needed as a last resort."

The third are provider-based transit initiatives such as vouchers, rideshare, or direct transportation services determined by program polices, funding and resources. These services may receive reimbursements, such as, private health insurance plans, employee assistance programs or direct billing. Providers discussed the use of rideshare companies, ride-hailing companies and the use of provider owned transportation vehicles.

During the time period when the advisory panel was meeting, one of the advisory panel multi-service providers identified and purchased a building near a major transit center in the City of Hartford. The same provider accepted the donation of a minibus to provide new direct transit service to and from their services and programs.

The group's efforts developed into a collaboration on a recent National Institutes of Health (NIH) funding announcement for their ComPASS program. As a part of this proposal, the community research team – consisting of individuals from the CT DMHAS, the Capitol Region Council of Governments, and a state-operated community clinic, together with the research partners at University of Connecticut and UConn Health – developed a 10-year plan. This plan included an intervention – called a "transit toolkit" – aimed at improving health outcomes of individuals seeking shelter in and/or near transit stations in Hartford and New Haven. This proposal is built upon some of the ongoing related work of DMHAS, and the goals of the University of Connecticut team's "Transit and Treatment" project. This ongoing DMHAS work is called "Transit HOP" and is a collaborative effort with the CT DOT and CT State Police. For the "transit toolkit" project, with a specific focus on the needs of people of color at these transit stations, the research team will offer behavioral health, substance use treatment, housing, and transit supports. If funded, this new NIH project will represent the culmination of earlier work by both DMHAS and the University of Connecticut, with an achievement of system alignment across the transit, housing, healthcare and public health sectors.

Discussion

We uncover new empirical evidence, using a cost efficiency analysis framework, related to system alignment between substance use treatment, transit, and public health. Specifically, we find that proximity to a new transit line has led to lower operating costs of treating additional substance use clients, for providers that are “close” to a new transit station after the opening of the line (“economies of scale”). We also find evidence that treating mental health and substance use clients together at one facility, for programs that are “close” to a new transit station, leads to lower operating costs (“economies of scope”). These findings are consistent with the “economies of scale/scope” findings of some other cost efficiency analysis studies, such as Cohen and Morrison Paul (2011). But prior cost efficiency studies have not considered the implications of economies of scale/scope for system alignment across transit, substance use treatment, and public health sectors. In the current study, while the new transit line may not have been intentionally aligned with the locations of the substance use treatment providers and programs, we argue that the results of this past alignment have important future implications for system alignment between substance use, mental health, and transit. Also, improved access is important for health equity. We convened an advisory panel of experts in the relevant sectors, which has been meeting monthly from May, 2020 to March, 2023 (and will continue meeting through December, 2023), to discuss system alignment strategies, past experiences, and challenges and limitations to system alignment approaches. Representatives of this panel include the CT Department of Mental Health and Addiction Services, the CT Department of Public Health, the CT Department of Transportation, the Capitol Region Council of Governments, 5 local treatment providers, and researchers from the University of Connecticut and UConn Health. One outcome of this advisory panel has been a major grant application to the National Institutes of Health ComPASS program. If funded, this follow-up project will build on past efforts of this “transit and treatment” and the “Transit HOP” projects to align substance use and behavioral health treatment with homelessness services, by bringing these services to transit stations and meeting individuals in need where they are in terms of their willingness to engage in treatment.

Our approach of exploring for past empirical evidence of system alignment success and projecting that forward to future system alignment efforts has the potential to be generalizable to other health care settings, besides the substance use treatment approach that has been considered in this paper.

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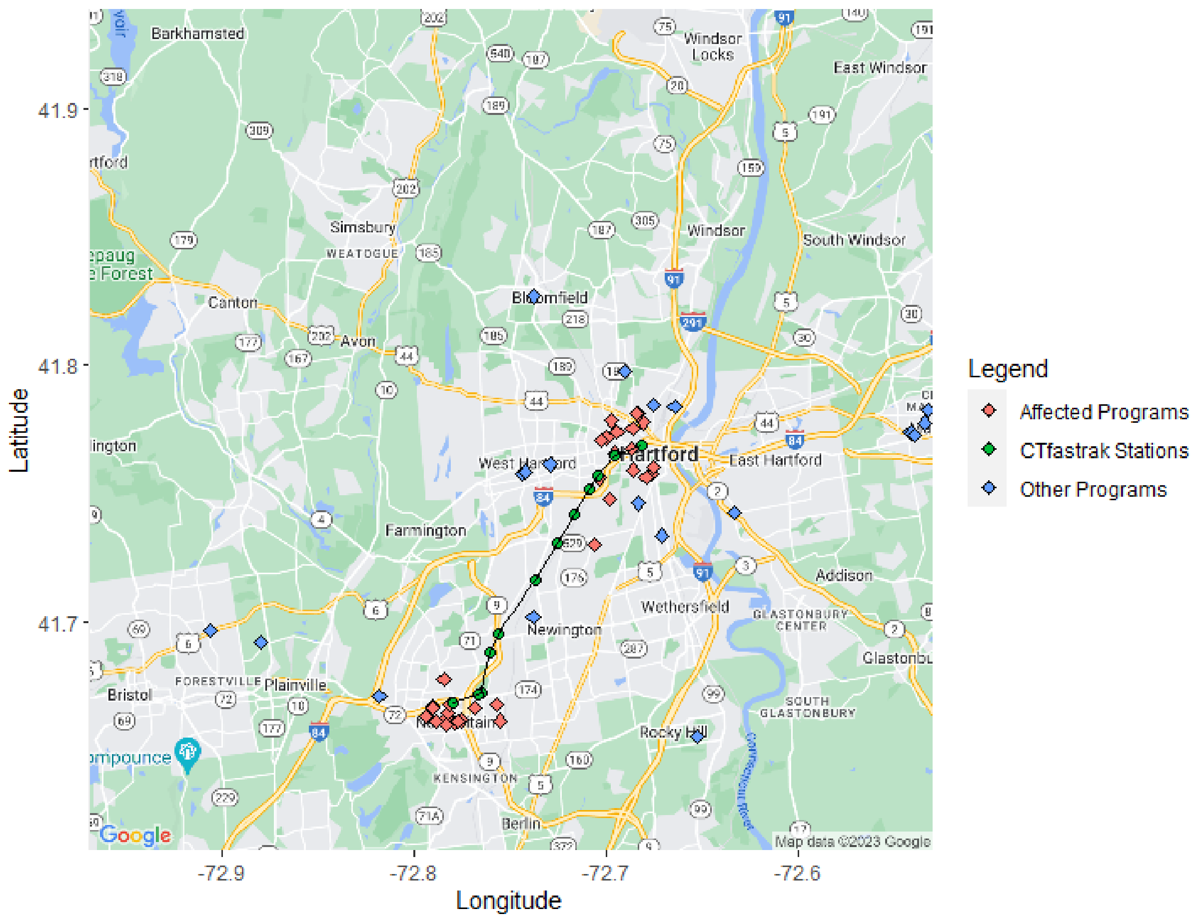
Figure 1. Locations of CTfastrak Transit Stations and Substance Use Treatment Programs



Note: Figure 1 shows map of Hartford, CT and surrounding areas with programs and CTfastrak stations labeled. Additional programs included in the study in regions beyond map not shown in figure. Affected programs are defined as those programs within one half mile of a CTfastrak Station opened in 2015. CTfastrak stations shown in green with solid line connecting stations. (Sources: CT DOT, CT DMHAS, and Authors' Calculations).

Table 1. Summary Statistics for Programs and Providers

	Mean	St. Dev.
Number of Clients per Programs per Year	86.4	248
Average values for Providers		
Total Operating Costs	23,835,567	19,993,850
Total Salary	10,356,922	11,025,185
Total Assets	12,808,726	11,324,051
Percentages of Clients by Provider		
Age 18-25	14%	8%
Age 26-34	20%	8%
Age 35-44	18%	5%
Female	43%	11%
African American	19%	13%
Hispanic	18%	9%
Percentages of Programs		
Client Treatment Completed %	35%	37%
Programs within .5 miles of new Station	6%	24%
Programs within .25 miles of new Station	5%	21%

Note: Data from Connecticut Department of Mental Health and Addiction Services Dashboard data from 2013-2018, combined with financial data from the Internal Revenue Service (IRS).

Table 2. Comparison of Cost-Total Client Volume Elasticity and Cost-Percent Completed Client Semi-Elasticity

Dependent Variable	log(OpCost)	log(OpCost)
Scale Elasticity Effect of New Transit	-0.024**	
	(0.011)	
Scale Semi-Elasticity Effect of New Transit		-0.200**
		(0.092)
Observations	1,534	1,435
R2	0.990	0.989

Note: In columns 1 and 2, the coefficients of interest are based on performing a (triple) difference-in-difference-in-differences regression of logged operating cost on client volume. The treatment effect variable is the product of a "near transit" (within 0.5 miles) indicator, an after transit opening (post-2015) indicator, and the provider's client volume. Scale elasticity (in column 1) represents the coefficient from a log-log specification, where client volume is the (log of) count of clients receiving treatment. Scale semi elasticity (in column 2) represents the coefficient from a regression where the dependent variable is logged and the volume variable is the proportion of clients completing treatment. These regressions include fixed effects for programs and years. Control variables are included for percent of provider's clients who are Black, who are Hispanic, who are female, who are in age groups 18-25, in age groups 26-34, and in age groups 35-44. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. The regression model uses data from Connecticut Department of Mental Health and Addiction Services from 2013-2018 combined with financial data from the IRS.

Table 3. Estimating Scope-semi-elasticity by Regressing Scope Variable on log Total Cost

	Dependent variable:	
	log(TotalCost)	
Scope Semi-Elasticity Effect of New Transit (Continuous)	-0.121**	
	(-0.056)	
Scope Semi-Elasticity Effect of New Transit (Binary)		-0.086**
		(-0.042)
Observations	1,337	1,337
R^2	0.990	0.990

Note: Coefficient of interest based on performing a (triple) difference-in-difference-in-differences regression of logged operating cost on client volume. Scope semi elasticity (continuous) represents the coefficient from a regression where the dependent variable is logged and the independent variable is the proportion of clients receiving multiple forms of treatment, multiplied by indicators for proximity to a transit station (within 0.5 miles) after the opening of the transit line (in 2015). Scope semi elasticity (binary) represents the coefficient from a regression where the dependent variable is logged and the independent variable is an indicator variable representing whether the program has any clients receiving multiple forms of treatment, multiplied by indicators for proximity to a transit station (within 0.5 miles) after the opening of the transit line (in 2015). This method includes fixed effects for programs and years. Control variables are included for percent of provider's clients who are Black, who are Hispanic, who are female, who are in age groups 18-25, in age groups 26-34, and in age groups 35-44. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. Column 1 gives a scope elasticity from comparing the percentage point change in proportion of clients receiving multiple types of care to the percentage change in operating costs for the provider. Column 2 gives another elasticity from comparing an indicator variable of if the program sees any clients who receive multiple forms of care to the percentage change in operating costs for the provider. The regression model uses Connecticut Department of Mental Health data from 2013-2018 combined with financial data from the IRS.

Appendix

Table A1: Demographic Determinants of log(OpCost)

log(nClients)	0.037*	0.0002
	(0.019)	(0.001)
Age18-25	7.227***	-0.272***
	(0.441)	(0.1)
Age26-34	-1.309**	0.292***
	(0.557)	(0.094)
Age35-44	-4.162***	0.547***
	(0.903)	(0.116)
Female	-0.523*	-0.319***
	(0.281)	(0.091)
African American	-2.717***	-0.097
	(0.247)	(0.094)
Hispanic	-0.366	-0.196***
	(0.372)	(0.061)
Program Fixed Effects	NO	YES
Observations	1,075	1,075
R^2	0.395	0.998

Note: Client demographics measured as proportion of all clients in all forms of treatment at program. *p**p***p<0.01

Table A2. Change in Program Cost-Volume Elasticity Using Different Sized Rings Around New CT FastTrack Stations

Dependent Variable Distance Indicator Value	log(OpCost) quartermile	log(OpCost) halfmile	log(OpCost) onemile	log(OpCost) twomile
log(nClients)	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
log(nClients)XdistIndicator	0.008**	0.008***	0.002	0.0003
	(0.003)	(0.003)	(0.002)	(0.002)
log(nClients)Xyearafter2015	0.003	0.003	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
distanceIndicatorXyearafter2015	-0.041	-0.03	-0.039**	-0.041**
	(0.028)	(0.027)	(0.017)	(0.017)
log(nClients)XdistIndicatorXyearafter2015	**-0.013***	**-0.015****	**0.002**	**0.005**
	(0.007)	**(0.007)**	**(0.005)**	**(0.004)**
Constant	17.558***	17.556***	17.526***	17.521***
	(0.035)	(0.035)	(0.035)	(0.035)
Observations	1,075	1,075	1,075	1,075
R2	0.998	0.998	0.998	0.998

Note: Coefficient of interest based on performing a difference-in-difference regression of operating cost on client volume. Scale elasticity represents the coefficient from a log-log specification. Coefficient in bold, log(nClients)XdistIndicatorXyearafter2015, represents the scale elasticity effect of the new stations across different distances between stations and programs. This method includes fixed effects for programs and years. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. Columns compare elasticities estimated from considering programs as affected based on varying distance from CTfastrak stations, using distances of quartermile (column 1), halfmile (column 2), one mile (column 3), and two miles (column 4). Elasticity estimated from comparing the percentage change in number of clients to the percentage change in operating costs. The model is regressed on data from Connecticut Department of Mental Health data from 2013-2018 combined with financial data from the IRS.

Table A3. Salary-Total Client Volume Elasticity and Assets-Total Client Volume Elasticity

Dependent Variable	log(Salary)	log(Assets)
ScaleElasticityEffectofNewTransit	-0.006	-0.055*
	(0.047)	(0.030)
Observations	1,527	1,534
R2	0.872	0.943

Note: Table A3 considers elasticity of salaries with respect to client volumes (column 1) and elasticity of assets to client volumes (column 2). The salary elasticity estimated is very close to zero and both elasticities are estimated with more uncertainty, suggesting that the change in elasticity of the new CTfastrak stations are not driven by salary and that more research on the relationship to assets may be useful. Coefficient of interest based on performing a (triple) difference-in-difference-in-differences regression of the cost variable on client volume. Scale elasticity represents the coefficient from a log-log specification. This method includes fixed effects for programs and years. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. Columns give an elasticity from comparing the percentage change in number of clients to the percentage change in salary and assets for the provider. The model is regressed on data from Connecticut Department of Mental Health data from 2013-2018 combined with financial data from the IRS.

Table A4. Comparison of Cost-Total Client Volume Elasticity, Cost-Completed Client Volume Elasticity, Cost-Clients Who Reduced Use Elasticity, Cost-Total Clients Employed Elasticity, Cost-Not Arrested Client Volume Elasticity, Cost-Self Help Client Volume Elasticity and Cost-Social Support Clients Employed Elasticity

Treatment Variable	NCompleted	nReduceUse	nEmployed	nNotArrested	nSelfHelp	nSocialSup
Dependent Variable	log(OpCost)	log(OpCost)	log(OpCost)	log(OpCost)	log(OpCost)	log(OpCost)
ScaleElasticity EffectofNewTransit	**-0.032***	**-0.017**	**-0.026**	**-0.010**	**-0.011**	**-0.013**
	(0.016)	**(0.023)**	**(0.019)**	**(0.024)**	**(0.027)**	**(0.013)**
Observations	775	300	865	300	327	456
R2	0.989	0.992	0.983	0.992	0.993	0.994

Note: Coefficient of interest based on performing a (triple) difference-in-difference-in-differences regression of operating cost on a volume variable. Scale elasticity represents the coefficient from a log-log specification. This method includes fixed effects for programs and years. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. Columns compare elasticities estimated from volume of different types of treatment. Elasticity estimated from comparing the percentage change in number of clients to the percentage change in operating costs. The model is regressed on data from Connecticut Department of Mental Health data from 2013-2018 combined with financial data from the IRS. The dependent variable in Table A4 is the total cost variable, but the health treatment variable changes. The health treatment variables are the volume of clients, the number of clients completing treatment, the number of clients who showed abstinence or reduced use, the number of clients who were employed, the number of clients not arrested, the number of clients who self-help (this variable is unclear to me), and the number of clients who get social support (also unclear to me).

Table A5. Comparison of Cost-Total Client Volume Elasticity for Mental Health Facilities and Addiction Programs

Treatment Variable	nClients	nNotArrested
Program Type	Addiction	Mental Health
ScaleElasticityEffectofNewTransit	**-0.018**	**-0.014**
	(0.022)	**(0.011)**
Observations	253	793
R2	0.998	0.998

Note: Coefficient of interest based on performing a (triple) difference-in-difference-in-differences regression of operating cost on a volume variable. Scale elasticity represents the coefficient from a log-log specification. This method includes fixed effects for programs and years. Standard errors in parenthesis. Significantly different than zero at 90 (*), 95 (**), 99 (***) percent confidence. Columns compare elasticities estimated from volume of different types of programs. Elasticity estimated from comparing the percentage change in number of clients to the percentage change in operating costs. The model is regressed on data from Connecticut Department of Mental Health data from 2013-2018 combined with financial data from the IRS. Table A5 splits programs into addiction programs and mental health programs and estimates the preferred model in each. There are more mental health programs (793) than addiction programs (253). Some providers have programs of both types, while some have only one or the other. In these cases, the elasticity variable is similar across program types, but the smaller sample size is one possible reason why the variable is not statistically significant.