RESEARCH ARTICLE

Use of Evidence-Based Substance Abuse Treatment Practices and Discretionary Government Funding

Business and Economics Journal, Vol. 2013: BEJ-65

Use of Evidence-Based Substance Abuse Treatment Practices and Discretionary Government Funding

Roberto A Trevino*, Alan J Richard[1]
College of Business, University of Houston-Downtown, Houston, TX, USA.
[1] RTH Research Group, LLC, Houston, TX, USA.

***Correspondence:** TrevinoRo@uhd.edu

Accepted: Dec 16, 2012; Published: Jan 03, 2013

Abstract
Most nonprofit drug treatment providers (DTPs) in the US rely on discretionary government funding (DGF) allocations in order to provide drug treatment services to uninsured clients. However, little is known about the factors associated with DGF funding of DTPs. Of particular interest is whether the use of evidence-based treatment practices (EBP) helps explain whether a DTP has DGF or not. EBP are treatment protocols that randomized, controlled research has indicated are more effective in reducing substance abuse disorders than standard treatment protocols. Although EBP are more effective than standard substance abuse treatment practices, many DTPs do not use EBP. This paper begins to fill this gap in research by examining whether DTPs that have DGF use EBP more often than DTPs without DGF. Using linear and hierarchical linear models, we analyze cross-sectional data on 6,062 private non-profit DTPs in 362 metropolitan areas participating in the 2009 National Survey on Substance Abuse Treatment Services (NSSATS). The results indicate that EBP use is positively and significantly associated with DGF in standard regression models, but the association is weakened and no significant when hierarchical linear models (HLM) are used. These results suggest that EBP are less solidly associated with DGF than may be optimal for the reinforcement of EBP adoption. Furthermore, the results suggest that other considerations compete with EBP in DGF allocations, weakening an already-fragile supply of EBP.

Keywords: Substance abuse treatment; evidence-based practices; discretionary government funding; behavioral health; hierarchical linear models.

1. Introduction

The appetite for illegal drug use in the US continues unabated despite increased legal penalties, accompanied by high social and economic costs. Estimates of the overall cost of substance abuse to the US economy exceed $600 billion a year [1]. The National Household Survey on Drug Use and Health (NSDUH) estimates that 10% of US adolescents and adults, an estimated 22.6 million Americans 12 years of age or older, used some type of illicit drug in 2010 [2]. Comparison of multi-year NSDUH data also indicates that illicit drug use has increased in the last few years, and that illicit drug use is concentrated in large metropolitan areas, primarily located in the West and in the Northeast.

At the same time, more than 20 years of research has shown that substance abuse treatment works [3]. Recognizing the persuasive power of the empirical evidence, US public health policymakers have sought to facilitate access to treatment services. In the US, substance abuse treatment is mostly provided by private non-profit and for-profit drug treatment providers (DTP). Treatment consumers with private insurance access treatment via behavioral health care carve-outs mostly at private for-profit DTPs. Consumers with public health insurance get treatment services via the Federal Medicaid and Medicare programs. In addition, the federal government allocates non-competitive block substance abuse treatment grants to States' governments in order to fill remaining gaps in treatment access and to help them finance treatment services. Finally, the federal government, along with some state and local governments, also allocates discretionary government funding (DGF) in the form of competitive grants directly to nonprofit DTPs. They use these funds to provide drug treatment services to low income and uninsured consumers seeking free or low cost treatment services. A recent study found that 2/3 of private nonprofits DTPs in the US depend on DGF grant allocations to be able to provide treatment services at low cost or free to urban poor clients who do not have private or public health insurance [4].

DGF application guidelines require DTPs to document the local need for the proposed services and how the requested funds will be used to address this need. Since research shows that substance abuse treatment is more effective when it is matched to an individual's specific antecedents for substance abuse [5-10] funding application guidelines also require applicants to match their selected practice to the target population that they propose to serve with the requested DGF. Reviewers of DGF grants are instructed to evaluate the outlined need for the requested funds. Often this need is documented with data showing the substance abuse prevalence in the community among a given subpopulation group, poverty, unemployment, socioeconomic status and their inability to access low-cost or free treatment services in a community. In addition, grant reviewers assess the application's selection of the proposed substance abuse treatment practice. Applicants that propose an evidence-based practice (EBP) for the treatment of substance abuse disorders and outline how the proposed EBP addresses the needs of the targeted population are likely to receive a higher score on the proposed practice criteria of their application. Although there are no standardized criteria for the point distribution in evaluating substance abuse treatment grants across all programs[1], DGF grant applications are usually evaluated on 100-point scale. Often, applications allocate 15 points to the description of local need; 35 points to the presentation of the proposed treatment practice; 15 points for proposed implementation plan; 20 points for staff and organization qualifications/expertise and about 15 points for evaluation of the services proposed. A score of 90 points or above generally implies that the applicant for DGF will be awarded most of the requested funds in their application. Therefore, the proposed treatment practice and expertise in that practice play key roles in determining DGF allocations, *ceteris paribus* need, program plan, staff and evaluation. The question this policy raises, then, is whether DTPs that use EBP are more likely to receive fundable scores and therefore to receive DGF on their applications than those that do not. Ideally, testing such hypothesis will require a dataset with data on all DTPs that have applied for funding during a given period, the practice each of these proposed, their expertise with and use of the proposed practice and the DGF outcome of each application. To our knowledge, however, such data are not publicly available. Therefore, the goal of this paper is to compare the use of EBP among those DTPs that have DGF to the use of EBP by those that do not, without implying causation between the use of EBP and allocation of DGF. By understanding the factors the help increase EBP among DTPs, public health policy will be enhanced. If DTPs that use EBP more often are more likely to have GDF, it will imply that the funding agencies may value efficiency more than need. However, if DTPs that use EBP more often are less likely to have DGF, it will imply that funding agencies may value other factors, such as need and/or equity, more than efficiency when considering DGF allocations.

With the rise of managed care in the early 1990's, behavioral health services researchers have been interested in examining how internal DTP factors affect several DTP processes and outcomes. For example, Olmstead and Sindelar [11, 12] examined the effects of managed care on substance abuse treatment availability. Montoya [13] studied the effect of DTP for-profit status on the supply of auxiliary drug treatment services; Mojatabaii [14] considered how DTP characteristics influence the supply of services for co-occurring disorders (mental health and substance abuse); Campbell and Alexander [15, 16] and Nahra [17] studied the effect of DTP ownership on access to treatment. Grella [18] and Brown *et al.* [19] analyzed the factors that influence women's access to treatment services. Bryan and colleagues [20] evaluated the availability of treatment services for gay and bisexual clients. Trevino and Richard [21] examined how competition affects the supply of specialized treatment services. This paper adds to this important area of research by studying whether the use of EBP differs between DTPs that have DGF and those that do not.

Economic theory suggests a number of perspectives on the need for DGF to help finance substance abuse treatment services. One might argue that since substance abuse treatment services are not a pure public good, being excludable and rival in consumption, a private market supply can emerge. But since lack of access to substance abuse treatment services causes negative externalities to all members of society via increased crime, emergency room use, and incarceration costs, one might argue that DGF for substance use is justified [22]. A second rationale for DGF of drug treatment services is poverty and low socioeconomic status, which creates an unmet need due to the inability of those in need to pay for services. However, providing DGF for substance abuse treatment services solely to minimize externalities or to address poverty concerns may not meet efficiency and cost-effective standards since the average unit cost of adequate substance abuse treatment for low-income consumers is higher than the average unit cost for higher income consumers [24]. Finally, public taste for direct DGF to DTPs may be viewed as a response to political governmental preferences, themselves a reflection of the preferences of the median voter in the State where DTPs are located [25].

[1] There are many different types of substance abuse treatment grants some target specific illegal drugs (methamphetamine, cocaine), while other grants target specific populations (youth, homeless, people at risk for HIV, minority populations).

If the rationale for DGF is satisfied, an equally difficult question arises: how to allocate the limited substance abuse treatment DGF available among the many DTPs in need of such funds. Two possible types' allocation criteria exist. The first one is based on horizontal equity. Horizontal equity suggests, for example, that DTPs located in two separate but equally needy (poor) geographical locations ought to receive the same level of DGF. The second type is derived from vertical equity. Vertical equity suggests that DTPs located in two areas with equal need would receive unequal DGF allocations. Thus, two different DTPs with equal need would receive unequal funding since there will be other catalysts for this decision, including whether or not DTPs use EBP. This paper begins to make a contribution to this limited area of research by examining differences in EBPs among DTPs that have DGF and those that do not.

2. Methods

Analyses used data from the 2009 National Survey of Substance Abuse Treatment Services (NSSATS). The dataset includes data on DTP characteristics such as ownership type (private non-profit, private for-profit or public), use of EBP, receipt of DGF and number of clients treated. In addition, the NSSATS indicates whether the facility is a substance abuse specialized facility and whether facility offers residential treatment as well as the percentage of clients who are dual diagnosed [26]. Nonprofit DTPs have three sources of revenue: competitive DGF, government-financed programs such as Medicaid, private clients and private donations. The data included in NSSATS collects aggregated competitive DGF allocations from Federal, State and/or local governments. The NSSATS data do not provide the specific amount of DGF. DGF is a dichotomous variable indicating whether or not the DTP has DGF or not (1=yes, 0=no). The NSSATS does not specify whether a DTP without DGF applied for DGF but failed to obtain it, or simply did not apply. Since the NSSATS data do not specify whether the DGF is from federal, state, or local government, the paper cannot analyze sensitivity of the DGF donor to the DTP use of EBP. This may be important, since it is possible that State DGF preferences are less elastic to the use of EBP than those of Federal DGF agencies. Notwithstanding this limitation, this paper begins to make a contribution by examining whether DGF is associated with the use of EBP.

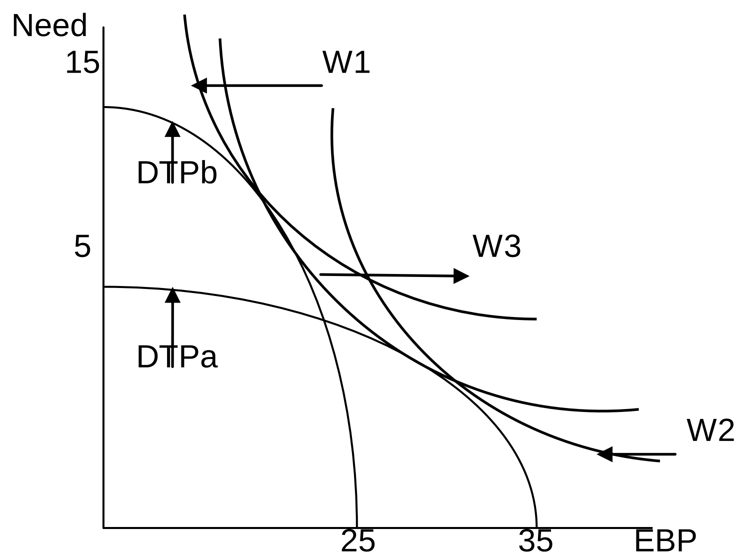
The dependent variable for this paper is whether or not a DTP currently has DGF (yes=1 or no=0). DGF is allocated directed to non-for-profit DTPs via a competitive grant process and does not include reimbursement revenue for treatment services rendered under Medicaid, Medicare and/or State health programs. The paper compares use of EBP among DTPs that have DGF versus those that do not. More specifically, the analysis focuses on five of the most supported behavioral EBP: 1) Cognitive Behavioral Therapy, 2) Motivational Enhancement Therapy, 3) Matrix Model Therapy, 4) Community Reinforcement Approach Therapy and 5) Rational Emotive Behavioral Therapy. An independent non-governmental agency designates practices as an EBP by evaluating clinical research studies on substance use and substance use-related outcomes of proposed EBP for specific populations. The designation of EBP is only bestowed once rigorous evaluation of these studies is completed. In addition, all EBP must have a manual available, and the developer of the practice must offer training on the practice. Currently there are about 12 behavioral EBP for the treatment of substance abuse disorders [27], but the NSSATS only collects information on the use of the five aforementioned EBP.

The theoretical framework for this paper is based on the work of Behrman and Craig [28, 29]. They examined the distribution and allocation of funding resources for police protection via a governmental social welfare function (W) specified as a Kohm-Pollak function. This function captures governmental preferences for efficiency vs. equity in the allocation of limited public funding resources. This paper measures efficiency by the use of EBP and equity by need for treatment services in the MSA, adjusting for DTP characteristics and State location of DTP. Specific research examining factors that influence funding allocations for non-profits is limited [30, 31]. Behrman and Craig argue that a funding agency welfare function (W) can be modeled as being dependent on two attributes, inequality aversion and unequal caring. In this context of this paper, the former refers to the dislike of the funding agency to having significant differences in DGF across metropolitan areas. The latter refers to the extent to which the funding agency prefers some DTPs (i.e., those using EBP) over others. This paper tests whether EBP use functions as such an unequal caring factor. The social welfare function (W) of the agency allocating the DGF is maximized subject to the production of treatment services and the funding agency budget constraints.

The aforementioned theoretical model can be illustrated with two DTPs (a and b), competing for DGF. Figure 1 illustrates the hypothetical situation. Both DTPs receive a score of 90 out of 100 on their application. The scores are identical on all categories except that DTP_a receives a score of 5 out of 15 on its need criteria (an exogenous factor to the DTP), and a score of 35 out of 35 on proposed practice (an endogenous factor to the DTP). DTP_a production is shown by DTP_a. DTP_b receives 15 points in its need criteria and 25 points on the proposed practice criteria (shown by DTP_b production). The social welfare function of the DGF agency is represented by W and is assume to be a function of inequality aversion and unequal caring on DGF allocations. The marginal rate of substitution between need and EBP determines the shape or concavity of the social welfare function. When the social welfare function is tangent to the DTP's production function, DGF will be allocated. Three possible social welfare functions are shown, W1, W2 or W3. If DTP_a receives DGF and DTP_b does not, then the agency funding behaves "as if" it values EBP more than need, as given by W2. If on the other hand, DTP_a does not get funding and DTP_b does, the funding agency behaves "as if" it values need more than EBP and its social welfare function will be given by W1. If both DTPs get DGF, then the funding preferences are valued equally and its social welfare function will be given by W3. When the DGF agency's social welfare function is maximized subject to the funding agency budget constraints, the following estimating equation is obtained:

Figure 1: DGF Allocations and DTPs Applications.

	Score	Need	EBP	Plan	Staff	Eva
DTPa	90	5	35	15	20	15
DTPb	90	15	25	15	20	15



$$(1) \qquad DGF_i = \beta_0 + \beta_1(EBP) + \beta_3(DTPCH) + \beta_4(MSASES) + \beta_5(STGOV) + \varepsilon_i$$

where subscript *i* denotes DTP and DGF is the binary dependent variable as measured by whether the DTP has DGF (1=Yes, 0=No). EBP is the mean frequency of use of the aforementioned five evidence-based treatment practices. Since only private non-profit DTPs are allowed to receive discretionary government funding, the analyses are based only on private non-profit DTPs. DTPCH is a vector composed of four variables designed to control for the characteristics of the DTP. DTPCH includes size of DTP (SIZE) as measured by the number of clients; whether the DTP specializes in substance abuse (SADTP); whether the DTP has residential services in addition to outpatient services (RESDTP) and the percentage of clients who are diagnosed with substance abuse and mental health problems (DUAL). DTPCH is a proxy for other potential omitted variables such as a DTP's ability to hire an effective grant writer and submit grant applications for funding, and a DTP's ability to pay for training on EBPs. For example, SIZE helps account for positive economies of scale. For example, larger DTPs may be better able to document and measure changes in clients pre-post outcomes than smaller size DTPs and thus they (larger DTPs) may be more likely to receive DGF since they will be better able to document their program's effectiveness to the funding agency.

SES measures the socio economic status of the metropolitan statistical area (MSA) where the DTP is located. SES includes the weighted MSA per-capita income, the percentage of the population with a college education, and the unemployment rate. American Public Health Association standards were used to calculate SES weights [32].

STGOV is a proxy to represent State tastes/preferences for direct DGF for substance abuse treatment. State preferences are measured by the extent to which State office holders are Democrats [33]. The state political index is the sum of how many of the three State local branches of government (Governorship, House, and Senate) are control by Democrats (1=yes, 0=no). The maximum value of STGOV will be 3 and the minimum will be 0. The political index measures aggregate voter's preference for a state and political affiliation of government officials has been shown to be a good proxy for the state median voter DGF preferences [34]. It is expected that local democratic power will be similar to the Federal representation for the States in those districts. Generally, Democrats represent greater support for direct DGF to DTPs [35]. Finally, ε_i denotes a random error term.

The next step in the analyses was to test for the appropriate empirical specification of equation 1 given that the data are geographically clustered. DTPs are nested within MSAs, which are nested within states, and shared market conditions or policy decisions at the MSA or state levels constitute potentially unmeasured sources of covariance. Hierarchical Linear Modeling (HLM) provides an appropriate method for analyzing data clustered in this way [36]. In multilevel models, fixed effects are identical for all groups in a population and random effects vary from group to group [37]. HLM has been used to address data clustering in studies of academic achievement among students nested within classes nested within schools, of employee job satisfaction when employees are nested within departments nested within firms, and of children's behavioral problems, when children are nested within families within communities.

In our analysis, DTPs were clustered at Level 1, MSAs were clustered at Level 2 and States were clustered at Level 3. For notation purposes, we will let Y denote the dependent variable (DGF). The first HLM model estimated (HLM1) is an unconditional model and it is specified as follows:

HLM1 Level 1: Prob(Y_{ijk}=1|π_{jk}) = ϕ_{ijk}; log[ϕ_{ijk}/(1- ϕ_{ijk})] = η_{ijk} and $\eta_{ijk} = \pi_{0jk}$. In this model the indices *i,j,k* denote DTPs, MSAs and States, respectively. Thus, for Level 1, Y_{ijk} measures whether DTP$_i$ in MSA$_j$, in State$_k$, received DGF. Y_{ijk} is a binary outcome (Yes=1, No=0) and is assumed to have a Bernoulli distribution and ϕ_{ijk} is the probability of success (yes) on m_{ijk} trails. That is, $Y_{ijk}|\phi_{ijk} \sim B(m_{ijk}, \phi_{ijk})$ and Y_{ijk} expected value and variance are given by: $E(Y_{ijk}|\phi_{ijk}) = m_{ijk}\phi_{ij}$ and $Var(Y_{ijk}|\phi_{ijk}) = m_{ijk}\phi_{ijk}(1-\phi_{ij})$, respectively. Lastly, since $\eta_{ijk} = \log\left(\frac{\phi_{ijk}}{1-\phi_{ijk}}\right)$, the predicted log-odds of $\eta_{ijk} = \exp(\eta_{ijk})$, yields a probability between 0 and 1, it can be estimated by $\phi_{ijk} = \left[\frac{1}{1+\exp(-\eta_{ijk})}\right]$.

HLM1 Level 2: $\pi_{0jk} = \beta_{00k} + r_{0jk}$ where β_{00k} is the mean of Y in State *k* and r_{0jk} is a random "MSA effect" which captures the deviation of MSA$_{jk}$'s mean from the State$_k$'s mean.

HLM1 Level 3: $\beta_{00k} = \gamma_{000} + u_{00}$ that is, β_{00k} is modeled as varying, randomly, around a grand mean, γ_{000}. The term u_{00k} is a random effect which captures the "State effect" or the deviation of State k's mean from the grand mean, γ_{000}.

Next, we estimate four 3-level conditional HLM models. HLM2 levels are given as follows: ***HLM2 Level 1***: Prob(Y_{ijk}=1|π_{jk})= ϕ_{ijk}; log[ϕ_{ijk}/(1- ϕ_{ijk})]=η_{ijk} and $\eta_{ijk} = \pi_{0jk} + \pi_{1jk}$*(EBP$_{ijk}$). EBP denotes the use of evidence-based practices by DTP$_i$ in MSA$_j$ in State$_k$. Level 2 and level 3 remain the same as in HLM1. **HLM3** is estimated while controlling, at level 1, for number of DTP clients (SIZE); whether the DTP specializes in substance abuse treatment services (SADTP); whether the DTP also offers residential services (RESDTP) and the percentage of clients who are diagnosed with substance abuse and mental health disorders (DUAL). Levels 2 and 3 remain the same as in HLM2. **HLM4** is estimated including MSA SES a controlling variable at level 2, but level 1 and level 3 remains the same as in HLM3. Finally, **HLM5** is estimated adding STGOV as a controlling variable at level 3. Level 1 and level 2 remain as in HLM4. Furthermore, for each of the HLM models aforementioned, substituting Level 3 in Level 2 and into Level 1 provides the mixed or fixed and random models used in the analyses.

3. Results and Discussion

3.1. Results

All models were estimated using data on 6,062 private non-profit DTPs in 362 MSAs with populations greater than 100,000 in all 50 US States and the District of Columbia. Table 1 shows the descriptive statistics of the data used in the analyses.

Table 1: Descriptive statistics.			
Variable	**Description**	**N=6,062**	**%**
DGF	DTP has Discretionary Government Funding (DGF)		
	Yes	4,359	71.9
	No	1703	28.1
EBP	Use of Evidence-Based Treatment Practices (EBP)		
	Low use of EBP	1425	23.5
	Medium use of EBP	2809	46.3
	High use of EBP	1828	30.2
SIZE	Number of clients		
	Small (less than 74 clients)	2956	48.7
	Medium (75-174 clients)	1532	25.3
	Large (175 or more clients)	1574	26.0
SADTP	DTP is substance abuse-focused provider		
	Yes	3916	64.6
	No	2146	35.4
RESDTP	DTP offers residential services and outpatient services		
	Yes	2152	35.5
	No	3910	64.5
DUAL	Percentage of clients who are dual-diagnosed		
	0-33%	2989	49.4
	34-66%	1581	26.0
	67-100%	1492	24.6
SES	Social Economic Status of MSA where DTP is located		
	Low	1281	21.1
	Medium	3831	63.2
	High	950	15.7
STGOV	Number of State Government Branches that are Controlled by Democrats		
	None	964	15.9
	One	1161	19.2
	Two	654	10.8
	All three	3283	54.1

As Table 1 indicates, about 70 percent of DTPs have DGF. Table 1 also shows the categorized mean frequency use of EBP. The dataset contains information about how often the DTP uses five specific EBPs (1=not very often, 4=very often). Thus the maximum mean EBP score is 4 and the minimum is 1. The average EBP use score was 2.65 out of a maximum score of 4. The EBP categories shown in Table 1 were obtained as follows: DTPs scoring from 1.00 to 1.99 were assigned a low EBP; DTPs scoring 2.00 to 2.99 were assigned a medium EBP use and DTPs scoring from 3.00 to 4.00 received a high EBP category. The EBP categories presented in Table 1 are for descriptive purposes only. The regression analyses used the uncategorized EBP score. Table 1 also shows the size of DTPs in the sample. As the Table shows almost half of DTPs were small with less than 75 clients. About 2 in 3 DTPs specialized in providing substance abuse treatment services only and only one in three of them also provided residential treatment services. In addition, almost half of the DTPs had less than 30% of dual-diagnosed clients (substance abuse and mental health). The socio economic status index (SES) of the MSA where the DTP is located was calculated by a weighted index composed of the unemployment rate in the MSA (45%), the per capita income in the MSA (25%) and the percentage of college graduates in the MSA (30%). SES is proxy for poverty and need for substance abuse treatment services in the area. SES scores ranged from 1.3 to 7.5. These scores were normalized to range from 0 to 1 and categorized as low when score was below 0.33 and high when score was above 0.66. As Table 1 indicates, most DTPs were located in MSAs with a moderate SES score. Lastly, about half of all DTPs (54%) were located in States where all three branches of State Government were controlled by Democrats. Only about 15% of DTPs (964) were located in State where Democrats did not have any control of State government. Again, the categorized variables (EBP and SES) presented in Table 1 are for descriptive purposes only. The regression analyses used the raw uncategorized scores.

Table 2 shows differences in DGF by EBP use. The results show that DTPs that used EBP more often were more likely to have public funding (p<0.05) than DTPs which did not use EBP often (79% vs 65%).

Table 2: DTP use of EBP and DGF.

EBP	DGF=Yes (N=4359)		DGF=No (N=1703)		Total (N=6062)	
	N	%	N	%	N	%
Low	922	21.2	503	29.5	1425	23.5
Medium	1993	45.7	816	47.9	2809	46.3
High	1444	33.1	384	22.6	1828	30.2

Next, we examined whether DGF varied across MSAs and States. The data analyses showed that there were statistically significant differences in DGF across levels of need (SES) and State governments (STGOV). First, DTPs located in poor MSAs (low SES) were statistically more likely to have DGF than similar DTPs located in MSAs with high SES scores (82% vs 68%). In addition, DTPs located in States where Democrats had greater control of State government were statistically more likely to have DGF than DPTs located in States where Democrats had less control of State government (85% vs 54%). These results suggest that DGF is more closely associated with DTPs serving poor communities in States where Democrats have a greater control of States government than among DTPs serving poor communities where Democrats have less control of State government. These results also suggest significant clustered-related variation at level 2 (SES) and level 3 (States). Thus, there is a need for HLM models.

Table 3 shows correlations among the variables of interest. The Table shows that EBP use is positivity correlated with larger DTPs and DTPs that offer residential treatment and have a higher percentage of dual diagnosed clients. On the other hand, EBP is negatively associated with DTPs that are substance abuse-focused, and those located in MSAs with high SES and in States with high Democratic control of State government. These results also suggest significant cluster-related variance at level 2 (MSA) and level 3 (States) while controlling for DTP use of EBP and DTP characteristics.

Table 3: Correlation analyses.

Variable	1	2	3	4	5	6	7
EBP	1.00						
SIZE	0.03	1.00					
SADTP	-0.06**	0.03*	1.00				
RESDTP	0.02	-0.21**	0.22**	1.00			
DUAL	0.10**	0.02	-0.25**	0.09**	1.00		
SES	-0.01	0.03*	0.00	-0.01	0.09**	1.00	
STGOV	-0.08**	0.05**	0.12**	-0.01	-0.02	0.27**	1.00

Note: *p<0.05, **p<0.01

Table 4 shows odds ratios obtained from the 2 logistic regressions analyses and on the 5 HLM regression analyses. Logistic regression odds ratio results (equation 1) are shown in column 2 and 3.

The logistic regression results show that the more frequent use of EBP significantly increases the odds of having DGF (p<0.05). The positive and significant relationship between the use of EBP and DGF is less clear, however, when HLM models are employed. Columns 4-8 of Table 4 show the results of the five HLM models estimated. The unconditional HLM model (HLM1) indicate that there are statistically significant (p<0.05) differences in the overall or grand mean (γ_{000}) of DGF among DTPs. Model HLM2 shows the effect of EBP use on DGF when EBP is included as an independent variable at Level 1. The results show that the value of phi (ϕ) which equals the probability of having DGF. In particular, the results show that DTPs that used EBP frequently were more likely (p<0.05) to have DGF than DTPs that did not use EBPs frequently. When DTP size was included as a controlling variable in the level 1 equation in HLM3, the results were robust. That is, more frequent EBP use remained significantly associated with having DGF (p<0.05). Results of HLM3 also show that DTPs that were larger, substance abuse focused and with residential services were more likely to have DGF than smaller, outpatient-services only and non-substance abuse focused DTPs. It is not clear from the results whether funding agencies prefer larger DTPs to smaller DTPs or whether larger DTPs applied for DGF more often than smaller DTPs given that larger DTPs may have a comparative advantage in applying for DGF given their economies of scale.

Table 4: Odds ratio regression fixed effect population-average model results [Confidence Intervals at 95%].

Variable	BL1	BL2	HLM1	HLM2	HLM3	HLM4	HLM5
Intercept (γ_{000})	0.88	5.94	2.70** [2.27-3.21]	0.80 [0.51-1.25]	0.46** [0.28-0.75]	0.18 [0.03-1.14]	6.73 [0.01-1.6]
EBP (γ_{100})	1.43** [1.31-1.56]	0.39* [0.09-1.65]		1.56** [1.33-1.83]	1.51** [1.33-1.72]	1.75 [0.97-3.15]	0.52 [0.08-3.38]
EBP x SES (γ_{110})		1.31 [0.98-1.75]				0.95 [0.85-1.01]	1.23 [0.84-1.82]
EBP X STGOV (γ_{101})		2.03** [1.14-3.60]					1.65 [0.77-3.55]
EBP x SES x STGOV (γ_{111})		0.86** [0.77-0.97]					0.90 [0.78-1.05]
SIZE (γ_{200})	1.00** [1.00-1.01]	1.00 [0.99-1.01]			1.00** [1.00-1.00]	1.00* [0.99-1.01]	1.00* [0.99-1.01]
SIZE x SES (γ_{210})		1.00 [0.99-1.00]				0.99 [0.99-1.00]	1.00 [0.99-1.00]
SIZE x STGOV (γ_{201})		0.99 [0.99-1.00]					0.99 [0.99-1.00]
SIZE x SES x STGOV (γ_{211})		1.00 [1.00-1.00]					1.00 [0.99-1.00]
SADTP (γ_{300})	1.43 [1.23-1.62]	1.74* [1.85-4.80]			1.83** [1.50-2.22]	3.23* [1.04-5.51]	1.09* [0.08-4.23]
SADTP x SES (γ_{310})		0.77 [0.52-1.12]				0.89 [0.72-1.11]	1.13 [0.67-1.90]
SADTP x STGOV (γ_{301})		0.57 [0.25-1.28]					1.22 [0.43-3.46]
SADTP x SES x STGOV (γ_{311})		1.10 0.93-1.28]					0.94 [0.77-1.16]
RESDTP (γ_{400})	1.82 [1.59-2.08]	1.42** [1.38-2.20]			1.41** [1.13-1.78]	3.10** [1.44-6.71]	4.41* [0.30-5.30]
RESDTP x SES (γ_{410})		0.66* [0.44-0.99]				0.85 [0.74-0.99]	0.77* [0.44-1.39]
RESDTP x STGOV (γ_{401})		0.59 [0.25-1.33]					0.89 [0.29-2.74]
RESDTP x SES x STGOV (γ_{411})		1.15 [0.98-1.35]					1.04 [0.83-1.31]
DUALCL (γ_{500})	0.99 [0.99-1.00]	1.01 [0.99-1.04]			0.99 [0.99-1.00]	0.99 [0.98-1.01]	1.00 [0.96-1.03]
DUALCL x SES (γ_{510})		0.99 [0.99-1.00]				1.00 [0.98-1.00]	0.99 [0.99-1.00]
DUALCL x STGOV (γ_{501})		0.99 [0.98-1.00]					0.99 [0.98-1.01]
DUALCL x SES x STGOV (γ_{511})		1.00 [0.99-1.00]					1.00 [0.99-1.00]
SES (γ_{010})	0.94* [0.87-1.01]	0.61 [0.26-1.43]				1.23* [0.87-1.74]	0.57* [0.18-1.79]
SES x STGOV (γ_{011})		1.31 [0.94-1.84]					1.29 [0.83-2.04]
STGOV (γ_{001})	0.99 [0.94-1.05]	0.28 [0.05-1.57]					0.27 [0.29-2.53]

Note: *p<0.05, **p<0.01

Although all of the above models support the hypothesis that the use of EBP is higher among DTPs that have DGF than among DPS that do not, the last two conditional models tell a different story. Model HLM4 indicates that, when MSA SES is added at Level 2, frequency of EBP use by a DTP is no longer significantly associated with having DGF ($p>0.05$). When State taste preferences are included in HLM5, the use of EBP remained non-significantly ($p>0.05$) related to having DGF. In summary, when non-cluster estimation methods are used, the results indicate a positive effect of EBP use on having DGF, but when cluster-sensitive methods are used, this effect appears to disappear. The results of the HLM models also show that there were statistically significant random effects of EBP use at level 2 (r_2) and level 3 (u_{20}), suggesting that there were potential random MSA and State effects not captured by the models as estimated.

3.2 Discussion

The question of whether and to what extent DGF should be allocated based on DTP use of EBP rather than need in the community lies at the heart of the public health policy debate. It can be argued that allocating DGF based on the use of EBP will be a more cost effective practice since it will achieve better and long lasting drug treatment outcomes including decreases in crime and health care costs. But allocation of DGF based on cost effectiveness alone may interfere with the policy goal of expanding access to treatment services of any type for all populations in need. Given today's limited commitment to public health spending, many governments have demonstrated a renewed interest in allocating DGF based on efficiency concerns rather than on need concerns. Market driven solutions are seen as a way to increase access and affordability of drug treatment services, even when these solutions may not result in allocation of DGF to areas most in need [38]. In defense of this practice, it could also be argued that DGF allocations which prioritize use of EBP rather over need will promote the use of EBP, increasing the quality of treatment available in the community. The purpose of this paper was to examine whether the use of EBPs differs between DTPs that have DGF and those that do not.

Although health services researchers have expressed an interest in examining the factors that increase EBP use, few studies have specifically examined how EBP differ among DTPs having DGF. Economic theory argues that DTPs will respond to incentives. Thus if DTPs suspect that public donors will link funding to EBP use, they are more likely to adopt EBP. Our data seem to indicate that donors continue to prioritize equity and poverty independently of EBP use. These results are consistent with previous research on allocation of school funding, showing that equity and fairness concerns motivate donor behavior and compete with concerns about outcomes [39]. Similar public funding effects have been reported in research on governance of non-profits [40].

This paper begins to examine whether frequency of EBP use increases the odds that a DTP will have DGF. The results showed that that use of EBPs is associated with DGF when MSA need (SES) and State taste preferences are not considered. However, once need (SES) and State preferences are included in the models (HLM4 and HLM5), EBP use is not associated with having DGF ($p>0.05$). This paper is one of very few in this area to specifically address the issue of multilevel clustered data, the issue of unmeasured covariance resulting from DTPs being nested within MSAs, which are in turn nested within States. When modeling EBP as an independent variable on DGF, ordinary regression analysis yields a result indicating a significant EBP effect but this analytical procedure violates the uncorrelated normality assumptions of the error terms. Failing to account for error among these three levels when analyzing the effects of EBP practices could lead to the Simpson paradox and Ecological fallacies. When we adjust for these statistical violations, no significant effects of EBP use on DGF are found, indicating that there is no independent relationship between DGF and EBP.

This paper centered on the use of EBP among private nonprofit DTPs and did not examine whether and how EBP use in public DTPs within an MSA affects EBP use in private DTPs. It could be argued that EBP use in public DTPs influences EBP use in private DTPs since the former crowd in the supply of EBP used. Further research should examine this and related questions. Third, the models examined only included one explanatory variable at levels 2 and 3. Much more refined model specification would be possible given an appropriate dataset. MSA socio-demographics could be included at level 2, for example. And at level 3, a State representation at the federal level could also be included. Such type of analyses was beyond the main purpose of this paper, but further research would do well to borrow from the rich political science literature in order to examine and estimate better measures of State preferences and regulatory substance abuse environment.

4. Conclusion

This paper begins to examine whether the use of EBP can help explain DGF allocations. Our results indicate that EBP use, while important, competes with other considerations such as equity and poverty in determining which DTPs have DGF. Balancing equity concerns with quality concerns is consistent with the written instructions donors prepare for peer reviewers. Reviewers are given some discretion, however, in determining the weight given to each concern. The results of this discretion impact the equity and quality of substance abuse treatment services on the ground. Disproportionate consideration of poverty or local DGF tastes could result in a two-tiered system, with low-quality services offered at low cost in low-income MSAs and high-quality services offered at a premium cost in wealthy MSAs. Disproportionate consideration of EBP use or other quality concerns could result in the unintended steering of DGF toward large institutions with the liquid resources to pay for professional grant writers and expensive EBP training, institutions generally not located in poor neighborhoods in MSAs with the most need. Either way, the weight given to equity over quality and vice versa may have adverse unintended consequences for poor or uninsured people with substance abuse disorders, the very people with the greatest unmet need for clinically effective (EPB) substance abuse treatment services.

Competing Interests

The authors declare that they do not have any competing interests.

Authors' Contributions

RAT conducted the data analyses and wrote the methods, results and draft of the manuscript. AJR conducted the literature review, wrote the discussion and conclusion sections, and edited the final draft of the manuscript.

References

1. Office of National Drug Control Policy (ONDCP), 2004. The economic costs of drug abuse in the United States, 1992-2002, [www.ncjrs.gov/ondcppubs/publications/pdf/economic_costs.pdf].
2. Substance Abuse and Mental Health Services Administration (SAMHSA), 2011. Results from the 2010 national survey on drug use and health: Summary of national findings, [http://oas.samhsa.gov/NSDUH/2k10NSDUH/2k10Results.htm].
3. McLellan T, O'Brien C, Metzger C, Alterman D, Cornish A, Urschel J, 1992. In *Addictive States.* Edited by O'Brien C and Jaffe J. Raven Press; New York, NY.
4. Trevino R, Richard A, 2012. Public funding and affordability of substance abuse treatment services. American Journal of Economics and Business Administration, 4(1): 72-83.
5. Ashley O, Marsden M, Brady T, 2003. Effectiveness of substance abuse treatment programming for women: a review. The American Journal of Drug and Alcohol Abuse, 29(1):19-53.
6. Greenfield L, Burgdorf K, Chen X, Porowski A, Roberts T, Herrell J, 2004. Effectiveness of long-term residential substance abuse treatment for women: findings from three national studies. The American Journal of Drug and Alcohol Abuse, 30(3): 537-550.
7. Claus RE, Orwin RG, Kissin W, Krupski A, Campbell K, Stark K, 2007. Does gender-specific substance abuse treatment for women promote continuity of care? Journal of Substance Abuse Treatment, 32(1): 27-39.
8. Niv N, Hser Y, 2007. Women-only and mixed-gender drug abuse treatment programs: service needs, utilization and outcomes. Drug and Alcohol Dependence, 87(3): 194-201.
9. Senreich E, 2010. Are specialized LGBT program components helpful for gay and bisexual men in substance abuse treatment? Substance Use & Misuse, 45(7-8): 1077-1096.
10. Grella CE, Stein JA, 2006. Impact of program services on treatment outcomes of patients with comorbid mental and substance use disorders. Psychiatric Services, 57(7): 1007-1015.
11. Olmstead TA, Sindelar JL, 2004. To what extend key services offered in treatment programs for special populations. Journal of Substance Abuse Treatment, 27: 9-15.
12. Olmstead TA, Sindelar JL, 2005. Does the impact of managed care on substance abuse treatment services vary by provider profit status? Health Services Research, 40(6): 1862-1882.
13. Montoya I, 2006. Differences in drug treatment services based on profit status. Journal of Psychoactive Drugs, 38(3): 219-228.
14. Mojtabai R, 2004. Which substance abuse treatment facilities offer dual diagnosis programs? The American Journal of Drug and Alcohol Abuse, 30(3): 525-536.
15. Campbell CI, Alexander JA, Lemak CH, 2009. Organizational determinants of outpatient substance abuse treatment duration in women. Journal of Substance Abuse Treatment, 37(1): 64-72.

16. Campbell CI, Alexander JA, 2006. Availability of services for women in outpatient substance abuse treatment: 1995-2000. Journal of Behavioral Health Services and Research, 33(1): 1-19.
17. Nahra TA, Alexander J, Pollack H, 2005. Influence of ownership on access in outpatient substance abuse treatment. Journal of Substance Abuse Treatment, 36(4): 355-365.
18. Grella C, Greenwell L, 2004. Substance abuse treatment for women: changes in the settings where women received treatment and types of services provided, 1987-1998. Journal of Mental Health Administration, 31(4): 367-383.
19. Brown JD, Vartivarian S, Alderks CE, 2011. Child care in outpatient substance abuse treatment facilities for woman: findings for the 2008 National Survey of Substance Abuse Treatment Services. Journal of Behavioral Health Services and Research, 38(4): 478-486.
20. Bryan CN, Peavy M, Robohm JR, 2007. Do specialized services exist for LGBT individuals seeking treatment for substance misuse? A study of available treatment programs. Substance Use and Misuse, 42(1): 161–176.
21. Trevino R, Richard A, 2012. The effect of competition on the supply of specialized substance abuse treatment services. AIMS International Journal of Management. Forthcoming.
22. Cuyler AJ, 2001. Equity - some theory and its policy implications. Journal of Medical Ethics, 27(23): 275-283.
23. Cuyler AJ, Wagstaff A, 1993. Equity and equality in health and health care. Journal of Health Economics, 12(4): 431-457.
24. Musgrove P, 1999. Public spending on health care: how different criteria related? Health Policy, 47: 207-223.
25. Raine R, Hutchings A, Black N, 2004. Is publicly funded health care really distributed according to need? The example of cardiac rehabilitation in the UK. Health Policy, 67(2): 227-235.
26. Substance Abuse and Mental Health Services Administration (SAMHSA), 2009. National survey of substance abuse treatment services (NSSATS). [http://wwwdasis.samhsa.gov/09nssats/nssats2k9web.pdf]
27. McGovern M, Carroll K, 2003. Evidence-based practices for substance use disorders. Psychiatric Clinics of North America, 26: 991-1010.
28. Behrman J, Craig S, 1987. The distribution of public services: An exploration of local governmental preferences. American Economic Review, 77(1): 37-49.
29. Craig S, Heikkila E, 1989. Urban safety in Vancouver: Allocation and production of a congestible public good. Canadian Journal of Economics, 4(22): 867-884.
30. Luksetich W, 2008. Government funding and nonprofit organizations. Nonprofit and Voluntary Sector Quarterly, 37: 434-442.
31. Henderson M, Whitaker G, Altman-Sauer L, 2002. Deciding to fund nonprofits: Key questions. Popular Government, 67(4): 33-39.
32. Duncan G, Daly M, McDonough P, Williams D, 2002. Optimal indicators of socioeconomic status for health research. American Journal of Public Health, 92(7): 1151-1157.
33. Leigh A, 2007. Estimating the impact of gubernatorial partisanship on policy settings and economic outcomes: A regression discontinuity approach. [http://hdl.handle.net/1885/47852]
34. Reed W, 2006. Democrats, Republicans, and taxes: Evidence that political parties matter. Journal of Public Economics, 90(4): 725-750.
35. Holcome R, 2006. Public Sector Economics. Pearson Prentice Hall, Upper Saddle River, NJ.
36. Raudenbush SW, Bryk AS, 2002. Hierarchical Linear Models: Applications and Data Analysis Methods. Sage Publications: Thousand Oaks, CA.
37. Gelman A, 2005. Analysis of Variance — Why it is more important than ever. Annals of Statistics, 33(1): 1–53.
38. Hacker JS, 2009. Healthy competition. The why and how of 'public-plan choice'. The New England Journal of Medicine, 360(22): 2269-2271.
39. Fahy C, 2011. Education funding in Massachusetts: The effects of aid modifications on vertical and horizontal equity. Journal of Education Finance, 36(3): 217-243.
40. Guo C, 2007. When government becomes the principal philanthropist: The effects of public funding on patterns of nonprofit governance. Public Administration Review, 67(3): 458-473.