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Economic Analysis of a Multi-Site Prevention Program: Assessment of Program Costs and Characterizing Site-level Variability

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Abstract

Programmatic cost analyses of preventive interventions commonly have a number of methodological difficulties. To determine the mean total costs and properly characterize variability, one often has to deal with small sample sizes, skewed distributions, and especially missing data. Standard approaches for dealing with missing data such as multiple imputation may suffer from a small sample size, a lack of appropriate covariates, or too few details around the method used to handle the missing data. In this study, we estimate total programmatic costs for a prevention trial evaluating the Strong African American Families-Teen program. This intervention focuses on the prevention of substance abuse and risky sexual behavior. To account for missing data in the assessment of programmatic costs we compare multiple imputation to probabilistic sensitivity analysis. The latter approach uses collected cost data to create a distribution around each input parameter. We found that with the multiple imputation approach, the mean (95% confidence interval) incremental difference was \$2149 (\$397, \$3901). With the probabilistic sensitivity analysis approach, the incremental difference was \$2583 (\$778, \$4346). Although the *true* cost of the program is unknown, probabilistic sensitivity analysis may be a more viable alternative for capturing variability in estimates of programmatic costs when dealing with missing data, particularly with small sample sizes and the lack of strong predictor variables. Further, the larger standard errors produced by the probabilistic sensitivity analysis method may signal its ability to capture more of the variability in the data, thus better informing policymakers on the potentially *true* cost of the intervention.

Keywords

cost(s); economic analysis; substance use prevention; youth; African Americans

Introduction

Economic analyses of prevention programs are increasingly common. While economic analyses of drug abuse treatment are abundant and have been extensively reviewed (Bray & Zarkin, 2006; Cartwright, 1998, 2000; French, 2000; French & Drummond, 2005; Ruger & Lazar, 2012; Schori, 2011), far fewer studies exist for drug abuse prevention (Guyl, Spoth, & Crowley, 2011; Holder, 2000; Mitchel, Hu, McDonnell, & Swisher, 1984; Pacileo & Fattore, 2009; Pentz, 1998; Plotnick, 1994; Spoth, Randall, Shin, & Redmond, 2005; Spoth, Guyl, & Day, 2002; Swisher, 2001; Swisher, Scherer, & Yin, 2004; Tricker & Davis, 1988). The accumulation of economic evidence is essential for policymakers to allocate scarce public resources across competing programs and interventions (Kellam & Langevin, 2003; NIDA, 2004; Popovici, French, & McKay, 2008). To achieve this goal, however, these analyses need to share a common methodology. Recognizing this, the Department of Health and Human Services convened a Panel on Cost-Effectiveness to form a common methodology for the conduct of such studies in medical settings (Gold, Siegel, Russell, & Weinstein, 1996). Their report offers a standard framework for ensuring that economic analyses of different interventions measure programmatic costs in a consistent manner.

However, prevention research raises a set of issues that may fall outside the scope of the Panel's work, as they typically involve delivery of programs in multiple sites in a variety of settings. Clinical trials of medications and medical procedures involve multiple sites as well, but tend to contain tight regulations. In contrast, between-site variability in intervention costs may be rather large in preventive interventions. There are often differences in program costs between sites that depend upon ecological parameters. For example, in the assessment of the Family Connections program (Corso & Filene, 2009), the authors found that the provision of the child maltreatment prevention intervention to different populations and services delivered by different providers, influenced programmatic costs across eight programs implemented nationally.

Even without significant ecological differences, one still might expect some level of variability within certain cost categories. Most behavioral interventions, including substance abuse prevention programs, rely heavily on personnel resources to implement the program (Pentz, 1998; Spoth et al., 2002); therefore, personnel cost is typically a key category for capturing variability in programmatic costs. Alternatively, there may be a cost category where one would not expect differences between the program being evaluated relative to the status quo (or control), but differences artificially appear. These cases may have a significant impact on the incremental difference in costs between the program and its control and if not accounted for could lead to spurious results.

This between-site variation and variability within cost categories is of interest for several reasons. First, it is important for characterizing the "typical" site. Second, the variation in costs may reflect differences in intervention delivery or the population served. Third, the variation may be associated with differences in program impacts. When considered together, understanding variability may help policymakers and other interested parties better understand possible changes to the program.

Unfortunately, these differences in costs may reflect other factors as well, such as the quality and availability of budgetary and other administrative data. Cost analyses require collection

of a wide range of cost categories (like space, materials, supplies, travel, training, etc.) and in the case of personnel costs, from a variety of individuals delivering the intervention. This reliance on individuals to agree to participate in the collection of costs or on well-kept administrative records often leads to missing data, causing difficulties when summing total programmatic costs. Before substantive issues shaping site differences can be explored, these differences must be understood and addressed. Otherwise, differences in the quality and availability of these data will confound differences due to substantive reasons.

Several technical challenges hinder efforts to calculate site-level costs and understand between-site variation. First, there are often few sites and statistical issues arise in relation to small sample sizes. While the central limit theorem maintains that sample means follow a normal distribution even when the underlying distribution does not, most statistical texts typically rely on a sample size of at least 30 to justify the theorem. As a result, a nonparametric method such as the bootstrap is often used to provide estimates of variability in these studies (Barlow et al., 2007; Doshi, Glick, & Polsky, 2006; Ettner et al., 2006; Rhiannon et al., 2007). Second, the underlying distribution of costs are commonly skewed, particularly when considering healthcare treatment costs (Briggs & Gray, 1998; Rutten-van Molken, van Doorslaer, & van Vliet, 1994). For example, healthcare costs typically have a high number of zeroes and a right-skewed tail, resembling a lognormal distribution. However, when considering aggregate program costs rather than person-level costs, as is often the case with preventive interventions, skewed distributions are a less common issue.

Finally, cost analyses often times do not provide discussion around handling missing data, and when the information is provided, the details tend to be scarce (Sterne et al., 2009). For example, for some of the substance abuse literature, either the researchers' best estimate was used to deal with missing data (Jones et al., 2009; Salome, French, Miller, & McLellan, 2003) or the researchers relied on a complete-case analysis (Jones et al., 2009; Woodward, Raskin, & Blacklow, 2008; Zarkin, Dunlap, & Homsy, 2004). According to Briggs, Clark, Wolstenholme, and Clarke (2003), many cost analyses use the available-case analysis, which does not allow standard statistical methods to be employed at the patient-level, even when data were collected in that way. Imputation is an alternative method for dealing with missing data, relying on other variables to estimate the missing values. Examples of imputation methods used within the economic evaluation of substance abuse intervention literature include (a) interpolation (Ettner et al., 2006), (b) mean imputation (Mojtabai & Zivin, 2003), (c) hot-deck imputation (Salome, French, Miller, & McLellan, 2003; Salome, French, Scott, Foss, & Dennis, 2003), and (d) multiple imputation (MI) (McCollister et al., 2009). MI is an iterative imputation method that predicts missing data from all relevant existing data (Royston, 2004; Schafer & Graham, 2002). MI includes a random component for each prediction to reflect the fact that each imputed value is an estimate (Brick & Kalton, 1996). Other imputation methods will tend to underestimate the variance around estimated values in subsequent statistical analyses by not taking into account the uncertainty involved when determining the "best" prediction of the missing value. Graham and Schafer (1999) found that using MI to deal with missing data performed as well as analyses with complete data for a sample size of 50 with missing data rates as high as 50%. Barnes, Lindborg, and Seaman (2006) also showed that MI analyses also performed reasonably well at sample sizes as low as 20. However, if a number of covariates (variables that correlate with the missing variable) or ecological parameters exist, a small sample size may restrict the number of parameters that can be included in the model. This is the case in many cost analyses of prevention programs, illuminating the potential need for an alternative method to MI in the presence of missing data.

Borrowing from methods typically recommended, and often times required, in economic analyses of health care interventions (Claxton et al., 2005; Drummond, Sculpher, Torrance,

O'Brien, & Stoddart, 2005; Weinstein, O'Brien, & Hornberger, 2003), one such alternative is probabilistic sensitivity analysis (PSA) (Critchfield & Willard, 1986; Doubilet, Begg, Weinstein, Braun, & McNeil, 1985; Mooney, 1997; Thompson & Graham, 1996). PSA involves sampling key model parameter values from prior distributions assigned to these model parameters. These prior distributions may arise from the published literature, some known statistical distribution, or from empirically collected data, where some data may be missing. Monte Carlo simulation is the process of randomly selecting values for each model parameter to arrive at a single cost and/or effect estimate. This process is repeated a number of times, each with a new combination of parameter estimates to create a probability distribution of the cost (or outcome). Although this is a common method in healthcare treatment costing applications where variability occurs at the patient level (Andronis, Barton, & Bryan, 2009) as described above, to our knowledge no studies have applied this method to community-level prevention programs, specifically in the assessment of prevention programs targeting substance abuse.

In this study, we compare two methods for summarizing programmatic costs of an intervention designed to prevent substance abuse, where some missing data for key cost categories exist. We first provide a brief overview of the context of the present cost analysis. Second, we outline our description for the MI and PSA procedures. Finally, we compare the pros and cons of each method and make a recommendation for future prevention studies assessing programmatic costs with missing data.

Methods

Study Sample

The present cost analysis was conducted prospectively in conjunction with the Rural African American Families Health Project, an individually randomized group treatment trial (Pals et al., 2008) designed to test the efficacy of the Strong African American Families—Teen (SAAF-T) program, a program designed to prevent substance abuse and sexual risk behavior in a rural African American population. SAAF-T is a form of *family skills training* (Kumpfer & Alvarado, 2003), an approach that integrates individual adolescent skill building, parenting skills training, and family interaction training. It consisted of five weekly meetings held at community facilities. Each meeting included separate, concurrent training sessions for parents and youth, followed by a joint parent–youth session during which families practice the skills they learned in their separate sessions. SAAF-T is currently being evaluated with ~500 families from rural communities in Central Georgia (Brody et al., 2012).

Participating families were randomly assigned to either the SAAF-T intervention or an attention control intervention (ACI). Participants were then assigned to a site within their respective county with meetings on either a weekday or a Saturday, depending upon the family's availability. Although intraclass correlation can be an issue with an individually randomized group treatment design such as this, our cost analysis focuses on site and not participant level costs and thus is not an issue we need to address.

The ACI was developed to mirror the SAAF-T intervention in terms of intervention modality and length. Developed loosely from an educational series called FUEL (<http://fuel.chef.org/>), the ACI focused on healthy diet and exercise. Trial participants resided in six rural counties in Georgia selected based on their rural nature (>50% of census tracts designated rural) and the number of African Americans living in the county (>20%). Community liaisons, African American community members living in the same counties as the participants, contacted youth identified from public school lists of 10th-grade students. Liaisons sent letters to the families and made follow-up phone calls to the primary

caregivers explaining the project and answering questions. Of the eligible families contacted, 79.4% agreed to participate. Final study participants included 502 African American youth in the 10th grade and their primary caregivers. Table 1 outlines demographic characteristics for the 199 families who participated in the two rounds of the intervention covered by this cost analysis. The participant dyads (one caregiver and one teen) assigned to SAAF-T or the ACI were similar with no statistically significant demographic differences as expected in a randomized design.

Programmatic Cost Data Collection

The majority of the costs related to the delivery of the SAAF-T and ACI interventions were collected prospectively during two rounds of intervention delivery at 16 sites in the four counties. Effort was made to adhere to the best practice guidelines outlined in the literature (Foster, Porter, Ayers, Kaplan, & Sandler, 2007; Haddix, Teutsch, & Corso, 2003). Program costs included in this analysis are personnel resources, non-personnel resources (site and ancillary services, supplies, equipment, and overhead), and participant costs. Costs were assessed at both the societal and provider perspectives. Societal costs include all costs, regardless of payer, needed to deliver the intervention and include the value of all resources expended, regardless if real or donated. Donated resources were valued at their commensurate market rate to reflect opportunity costs of their use. The provider perspective included only the value of real (not donated) resources required to deliver the intervention. Whenever possible, cost data were estimated from actual expenditures and not budget documents, as budgets oftentimes overestimate or underestimate the actual cost (Haddix et al., 2003).

Table 2 outlines the cost categories included in this study, the average cost per site, and indicates which categories were included in each study perspective. For facilitator and prevention supervisor time, site and ancillary services, facilitator transportation, and training categories, single point estimates were collected for each site. Some of these costs are a single site estimate, such as the amount paid to rent the building for the site, while other costs are an aggregate cost, such as the time spent making home engagement visits to each family by a facilitator. For all other costs, outside of participant costs, an aggregate cost was determined and a single estimate allocated to each site, such as the total CFR administrative time specific to SAAF-T for a specific round, allocated equally to each site in that round. All costs were collected in 2009 US dollars. The discount rate for amortizing costs spread over multiple rounds of the intervention was 3%, based on guidelines from the US Panel on Cost-effectiveness in Health and Medicine (Gold et al., 1996).

Personnel Resources

Personnel time was collected prospectively using time logs and surveys. Full-time administrative staff filled out daily logs while part-time personnel returned weekly logs. Facilitators were persons living in the communities who carried out the home engagement visits and led the intervention sessions. Facilitators were recruited to fill out weekly time logs; n=26 (54%) agreed to participate and completed the data collection process. There were no significant differences between facilitators choosing to participate and those choosing not to participate, based on range of experience or gender. Facilitators were supervised by a full-time administrative staff member who assisted with logistics and by a prevention supervisor, assigned to each group of facilitators. Prevention supervisors were experts in the intervention curricula and were assigned to provide regular support to each facilitator. Prevention supervisors were also asked to fill out time diaries at the end of each intervention round; n=9 (56%) participated. All research specific time was excluded from the final analysis and salaries including fringe benefits were used to determine the value of personnel resources.

Non-Personnel Resources

Non-personnel resources included site and ancillary services, supplies and equipment, overhead, and transportation-related costs. Inspection of site agreements and billing documents provided expenditure information for site rental costs, local site assistants, catering, childcare and transportation provided to families. For the societal perspective, donated space was valued at the market rate for that same or similar space. For the provider perspective, the value of donated sites was zero. Supply costs included the value of all materials provided to each site with cost estimation based on available receipts and internet searches for the items when receipts were not available. Travel costs were assessed using time logs and the conversion of personnel time to costs as described above. The provider perspective does not include all transportation time, only compensated time. The standard reimbursement rate for the state of Georgia at the time of intervention delivery (\$0.585 per mile) was applied to all travel (SAO, 2009). Overhead costs, for the general operations of the intervention administration, were split between SAAF-T and the ACI based on the intensity of time spent by the UGA administrative staff on intervention-related activities.

Participant Costs

The value of time spent participating in the program (identified through attendance records) encompasses the economic costs to participants, an important, yet often overlooked component of program costs. Caregiver time was valued using their reported wage rate or the minimum wage in Georgia, \$6.55 per hour (GDOL, 2007), as a proxy for the value of time for a caregiver who either did not report their salary or reported being a non-wage earner. Teen time was also valued at \$6.55 per hour, regardless of the family's monthly income. The mean (range) number of families for SAAF-T was 12.6 (5–17) and for ACI was 12.1 (9–15).

Analysis

This cost analysis included two models, MI and PSA, to determine the mean cost of the intervention and its subsequent variability. Both models created a total site cost that is the sum of the 36 cost categories, 11 of which had missing data. The construction of the site level costs provided the basis for how the two models differ. The first method, MI, imputed missing data for sites within each cost category and summed across categories for each site. The second method, PSA, used only the collected data (no imputation), created “modeled” sites by a random selection of costs from each category, and summed across categories for each modeled site.

Multiple Imputation (MI)

The missing values for each of the 16 sites were determined by MI, using the *mi impute chained* command in STATA (StataCorp, 2011). The truncated regression method with a lower bound at zero was utilized rather than the traditional regression method to eliminate instances of imputed negative costs. MI is a valid method for dealing with these missing data because (a) no sites were missing all cost data, (b) all sites had complete covariate data, (c) the predictor variables were moderately correlated, and (d) the numbers of these predictors were never too large compared to the sample size. The overall rate of missing data for the 11 cost categories that required imputation was 0.375 (0.188–0.531, range by cost category). Missing data resulted from facilitators and prevention supervisors that did not agree to participate in the cost collection process. There were no statistically significant differences between the following parameters that identify the intervention facilitators (p-value from χ^2 test): first time as a facilitator (0.321), experience (0.336), home engagement lead (0.838), intervention lead (0.152), or leader of parent versus teen sessions (0.152). Univariate imputation of each cost category included the following covariates: a dummy

variable signifying SAAF-T/ACI, whether or not groups met during the week or on the weekend, the number of families assigned to the group, facilitator experience, and a dummy variable signifying whether or not the facilitator was working at more than one site during that round. The facilitator experience and working multiple sites variables were only used when imputing facilitator time; the other covariates were used for imputing all of the variables. Furthermore, the reimbursed transportation costs, for which data were not missing, were strong predictors of the non-reimbursed transportation costs, and served as predictors for the transportation categories.

Resulting from the imputation procedure were $M=20$ complete datasets from which total programmatic costs were determined. A comparison of statistics on key variables before and after imputation is available upon request of the authors. The small sample size ($n=8$ sites) for each intervention arm makes normal theory methods, such as a Student's t-test and corresponding confidence interval, suspect as an estimate of variability. Instead, total programmatic costs were bootstrapped by resampling with replacement 10 000 times, the same choice for iterations made by Ettner et al. (2006) and a point beyond which successive iterations did not lead to appreciable changes in the mean. As a result, there are 20 values of the statistic of interest, one from each complete, imputed dataset. The mean and standard deviation of the bootstrap distribution provided estimates of the sample's mean and standard error, respectively (Efron & Tibshirani, 1993). The combination rules outlined by Rubin (1987) and implemented in STATA (Carlin, Galati, & Royston, 2008) for combining results from a repeated analysis were utilized to determine an estimate for the mean cost of each intervention arm, the difference in cost between the two arms, and corresponding 95% confidence intervals.

Probabilistic Sensitivity Analysis (PSA)

With the PSA approach for dealing with missing data, rather than imputation of missing data, the creation of modeled sites utilized only the collected cost data. Using a Monte Carlo simulation, the construction of each modeled site occurred through random selection of appropriate values for each cost category. The simulation randomly sampled from the array of costs in each cost category. The process was repeated a number of times to create a distribution of total site costs. We found that transportation costs, and to a lesser degree the site rental costs, were strongly biased toward sites in the control arm (i.e. transportation costs were larger for the ACI, narrowing the gap between the two interventions), yet there is nothing inherent in the interventions to suggest this bias. To correct for this bias, costs were selected from an array that includes collected costs from both programs for categories where there should not be a difference in cost between the two programs. For other cost categories, costs were selected from an array that includes collected costs from only the relevant program. The categories in Table 2 with totals included only under the "Combined" heading indicate categories for which costs were selected from an array including collected costs from both programs.

Furthermore, we explored two different approaches for randomly selecting costs from each cost category, both based on empirical data. The first gave each value in the array an equal probability of being selected. The second selected from a bootstrap distribution of available values, converting the empirical values into a statistical distribution. To create the bootstrap distribution for each cost category, costs from the original array were sampled with replacement a large number of times and the mean value from each replacement is saved, creating the distribution. Following selection, total programmatic costs were determined for each modeled site in the same way as for the MI procedure, by summing across all cost categories.

Results

Table 2 includes a breakdown of the programmatic costs for the cost categories included in this analysis (based solely on collected costs). The major cost categories that had the largest impact on the total costs (SAAF-T, ACI) for either intervention arm were personnel time (\$4318, \$3655), site and ancillary services (\$2814, \$2791), transportation (\$1764, \$1764), and training (\$2997, \$1291). The overhead (\$563, \$504) supplies and equipment (\$718, \$694) categories provided smaller overall contributions to the total cost. Furthermore, the training costs provided the largest contribution to the incremental difference in costs, primarily through the intervention training. Personnel time also contributed significantly to the incremental difference with the largest difference between the intervention facilitators.

Table 3 reports the MI results of total programmatic costs at the site level. The mean (95% CI) total programmatic costs from the societal perspective for one site of SAAF-T was \$16 251 (\$14 792, \$17 710) and \$14 102 (\$13 119, \$15 085) for the ACI, resulting in an incremental difference of \$2149 (\$397, \$3901) comparing SAAF-T to the ACI. Total programmatic costs from the provider perspective were roughly 20% lower following the removal of participant and non-compensated travel time from the model. The mean total programmatic costs from the provider perspective for one site of SAAF-T was \$13 478 (\$12 641, \$14 316) and \$11 531 (\$10 701, \$12 360) for the ACI, resulting in an incremental difference of \$1948 (\$777, \$3118) comparing SAAF-T to the ACI.

Table 3 also reports the PSA results. For each intervention arm, 10 000 modeled sites were created via random selection of costs from all relevant cost categories. The choice for the number of iterations corresponds with the number used for handling variability at the site level. The 95% confidence intervals arose from percentiles of the resulting distribution. The mean total programmatic costs from the societal perspective for one site of SAAF-T was \$16 405 (\$13 871, \$19 082) and \$13 854 (\$11 689, \$16 210) for the ACI, resulting in an incremental difference of \$2552 (–\$949, \$6033) when comparing SAAF-T to the ACI. Similarly, when values were selected from a bootstrap distribution, total programmatic costs for SAAF-T were \$16 419 (\$14 987, \$17 884) and \$13 836 (\$12 768, \$14 924) for the ACI, resulting in an incremental difference of \$2583 (\$778, \$4346) comparing SAAF-T to the ACI. Total programmatic costs from the provider perspective based on selection from a bootstrap distribution were \$12 965 (\$11 931, \$13 935) and \$10 558 (\$10 114, \$11 024) for SAAF-T and the ACI, respectively, a difference of \$2407 (\$1258, \$3476).

Discussion

The MI method produced a mean site difference in societal costs of \$2149. This estimate is over \$400 less than that produced by the PSA method (\$2583) with selection from a bootstrap distribution. The PSA method created a distribution of modeled total site costs by selecting values for each cost category from an empirical prior distribution. To account for the artificial leveling of the incremental difference in costs, the prior distribution included costs collected from both SAAF-T and the ACI for cost categories whose values were not explicitly dependent upon from which of the two interventions they were collected. For a category such as facilitator transportation, the few high values collected from the ACI sites, that also narrowed the incremental difference in the MI method, affected the result for the estimates of both SAAF-T and ACI “modeled sites” in the PSA method, rather than just for the ACI in the MI method. This inclusion should provide a better estimate of the *true* cost of the intervention for policymakers as the transportation costs were not specifically dependent upon the framework of either the SAAF-T or ACI interventions, but rather the framework of the Rural African American Health Project. As a result, the PSA method provided a larger incremental difference than the MI method. Furthermore, the greater standard errors

(\$1760/\$913 vs. \$693) produced by the PSA method may signal its ability to capture more of the variability in the data, thus better informing policymakers on the potentially *true* cost of the intervention.

Our experience collecting cost data from this prevention program, and another (Corso & Filene, 2009), leads us to a number of recommendations for improving availability of all program cost data (thus avoiding the issues of missing data). First, program data such as personnel time, space and utilities, supplies and equipment, training, travel, and participant time and other costs should be collected prospectively. To capture all programmatic cost categories and personnel activities required for the prevention intervention, we recommend engaging administrative and intervention delivery personnel early in the study design process. Retrospective cost collection can be affected by poor record keeping and study design flaws that cannot be corrected. Second, collection of costs from multiple sites can be improved if one person is designated as the data collector across all sites. This allows for consistency in reporting and coordination of efforts. Third, the system for collecting time diaries from providers should be as user-friendly as possible. Interventionists delivering prevention programs are already working at capacity; thus, giving them an easy system for reporting their time will lessen their burden and ensure completion of the data collection process. Finally, we recommend additional compensation to providers for completing programmatic cost collection activities. These reimbursements should be handled separately by the researcher and outside of their regularly scheduled wages to ensure accuracy of reporting.

Policymakers need programmatic costs and the associated variability to allocate resources efficiently. Because federal funding has emphasized treatment, few data are available on the costs of substance abuse prevention programs (Andlin-Sobocki, 2004; French & Martin, 1996; Machado, 2005), even though the potential economic efficiency of well-developed prevention programs targeting substance abuse has been established (Miller & Hendrie, 2008). This study also addressed four of the Blue Ribbon Panel on Health Services Research's recommendations for priorities in economic analyses of prevention programs (NIDA, 2004). First, this study illustrates programmatic cost analysis conducted alongside an individually randomized group treatment trial of a substance abuse prevention intervention. Second, the SAAF-T program is specifically designed for rural African American youth, a particularly vulnerable population. Third, programmatic costs were accurately determined and properly delineated through the description of included cost categories and their collection, along with the categorical totals provided in Table 2. Fourth, the comparison of analytic methods for handling variability in the presence of missing cost data could serve as a guide for other researchers conducting economic analyses alongside evaluation trials. Finally, the PSA method coincides well with French and Drummond (2005) who expanded on the Panel's recommendations, proposing greater incorporation of PSAs to better characterize uncertainty in economic evaluations of substance abuse related programs.

Limitations to the methods employed should be considered. First, the MI method is limited by having only a few well-correlated variables to guide the imputation, coupled with a relatively small sample. This situation is common for prevention and is an additional reason why the PSA method is viable. Second, with the PSA method, one cannot assign programmatic costs to individual participants in the intervention. Therefore, even if one had participant-level outcomes, many commonly used fully stochastic methods of analysis are impossible because both costs and outcomes cannot be tied directly to participants. Conversely, an important benefit of the MI method is the ability to take aggregate programmatic cost data and assign it to individual participants in the study. This is an important feature of fully stochastic cost-effectiveness analysis (CEA), whereby the

assessment of the CEA ratio is based both on the variability of the participant level outcomes and the participant level costs. In non-clinical settings, however, outcomes are often not available at the participant level, leaving PSA as a valid method for determining incremental cost differences and confidence intervals for these types of interventions.

Despite the limitations, our analysis illustrates how a method uncommon in prevention work can be utilized to determine total programmatic costs and incremental differences in costs between programs. Furthermore, studies reporting programmatic costs, especially for prevention interventions, typically have either ignored missing data (perform analysis on complete cases only) or imputed the missing data without reporting enough information about the analysis. To better handle missing data, studies should consider the reporting recommendations of Sterne et al. (2009) as were followed in this study. Finally, to better characterize variability, prevention studies with smaller sample sizes and significant amounts of missing data should consider methods such as PSA.

References

- Andlin-Sobocki P. Economic evidence in addiction: A review. *The European Journal of Health Economics*. 2004; 5(S1):s5–s12. [PubMed: 15754074]
- Andronis L, Barton P, Bryan S. Sensitivity analysis in economic evaluation: An audit of nice current practice and a review of its use and value in decision-making. *Health Technology Assessment*. 2009; 13(29):1–84.
- Barlow J, Davis H, McIntosh E, Jarrett P, Mockford C, Stewart-Brown S. Role of home visiting in improving parenting and health in families at risk of abuse and neglect: Results of a multicentre randomised controlled trial and economic evaluation. *Archives of Disease in Childhood*. 2007; 92:229–233. [PubMed: 17068074]
- Barnes SA, Lindborg SR, Seaman JW. Multiple imputation techniques in small sample clinical trials. *Statistics in Medicine*. 2006; 25:233–245. [PubMed: 16220515]
- Bray JW, Zarkin GA. Economic evaluation of alcoholism treatment. *Alcohol Research & Health*. 2006; 29:27–33. [PubMed: 16767850]
- Brick JM, Kalton G. Handling missing data in survey research. *Statistical Methods in Medical Research*. 1996; 5:215–238. [PubMed: 8931194]
- Briggs A, Clark T, Wolstenholme J, Clarke PM. Missing....Presumed at random: Cost-analysis of incomplete data. *Health Economics*. 12:377–392. [PubMed: 12720255]
- Briggs A, Gray A. The distribution of health care costs and their statistical analysis for economic evaluation. *Journal of Health Services Research & Policy*. 1998; 3:233–245. [PubMed: 10187204]
- Brody GH, Chen YF, Kogan SM, Yu TY, Molgaard VK, DiClemente RJ, Wingood GM. Family-centered program deters substance use, conduct problems, and depressive symptoms in black adolescents. *Pediatrics*. 2012; 129:108–115. [PubMed: 22157131]
- Carlin JB, Galati JC, Royston P. A new framework for managing and analyzing multiply impute data in stata. *Stata Journal*. 2008; 8:49–67.
- Cartwright WS. Cost-benefit and cost-effectiveness analysis of drug abuse treatment services. *Evaluation Review*. 1998; 22:609–636. [PubMed: 10186896]
- Cartwright WS. Cost-benefit analysis of drug treatment services: Review of the literature. *The Journal of Mental Health Policy and Economics*. 2000; 3:11–26. [PubMed: 11967433]
- Claxton K, Sculpher M, McCabe C, Briggs A, Akehurst R, Buxton M, Brazier J, O'Hagan T. Probabilistic sensitivity analysis for nice technology assessment: Not an optional extra. *Health Economics*. 2005; 14:339–347. [PubMed: 15736142]
- Corso P, Filene JH. Programmatic cost analysis of the family connections program. *Protecting Children: A Professional Publication of American Humane*. 2009; 24(3):78–88.
- Critchfield GC, Willard KE. Probabilistic analysis of decision trees using monte-carlo simulation. *Medical Decision Making*. 1986; 6:85–92. [PubMed: 3702625]

- Doshi JA, Glick HA, Polsky D. Analyses of cost data in economic evaluations conducted alongside randomized controlled trials. *Value in Health*. 2006; 9:334–340. [PubMed: 16961551]
- Doubilet P, Begg BC, Weinstein MC, Braun P, McNeil BJ. Probabilistic sensitivity analysis using monte carlo simulation: A practical approach. *Medical Decision Making*. 1985; 5:157–177. [PubMed: 3831638]
- Drummond, MF.; Sculpher, MJ.; Torrance, GW.; O'Brien, BJ.; Stoddart, GL. *Methods for the economic evaluation of health care programmes*. 3rd ed.. Oxford: Oxford University Press; 2005.
- Efron, B.; Tibshirani, RJ. *An introduction to the bootstrap*. Vol. 57. New York, NY: Chapman & Hall; 1993.
- Ettner SL, Huang D, Evans E, Ash DR, Hardy M, Jourabchi M, Hser YI. Benefit-cost in the california treatment outcome project: Does substance abuse treatment "pay for itself"? *Health Services Research*. 2006; 41:192–213. [PubMed: 16430607]
- Foster EM, Porter MM, Ayers TS, Kaplan DL, Sandler I. Estimating the costs of preventive interventions. *Evaluation Review*. 2007; 31:261–286. [PubMed: 17478629]
- French MT. Economic evaluation of alcohol treatment services. *Evaluation and Program Planning*. 2000; 23:27–39.
- French MT, Drummond M. A research agenda for economic evaluation of substance abuse services. *Journal of Substance Abuse Treatment*. 2005; 29:125–137. [PubMed: 16135341]
- French MT, Martin RF. The costs of drug abuse consequences: A summary of research findings. *Journal of Substance Abuse Treatment*. 1996; 13:453–466. [PubMed: 9219142]
- GDOL. Minimum wage change. 2007 2009, from http://www.dol.state.ga.us/spotlight/sp_minimum_wage_change_2007.htm.
- Gold, MR.; Siegel, JE.; Russell, LB.; Weinstein, MC., editors. *Cost-effectiveness in health and medicine*. New York, NY: Oxford University Press; 1996.
- Graham, JW.; Schafer, JL. On the performance of multiple imputation for multivariate data with small sample sizes. In: Hoyle, RH., editor. *Statistical strategies for small sample research*. Thousand Oaks, CA: Sage Publications; 1999.
- Guyll M, Spoth R, Crowley DM. Economic analysis of methamphetamine prevention effects and employer costs. *Journal of Studies on Alcohol and Drugs*. 2011; 72:577–585. [PubMed: 21683039]
- Haddix, AC.; Teutsch, SM.; Corso, PS. *Prevention effectiveness: A guide to decision analysis and economic evaluation*. 2nd ed.. New York: Oxford University Press; 2003.
- Holder HD. Community prevention of alcohol problems. *Addictive Behaviors*. 2000; 25:843–859. [PubMed: 11125775]
- Jones ES, Moore BA, Sindelar JL, O'Connor PG, Schottenfeld RS, Fiellin DA. Cost analysis of clinic and office-based treatment of opioid dependence: Results with methadone and buprenorphine in clinically stable patients. *Drug and Alcohol Dependence*. 2009; 99:132–140. [PubMed: 18804923]
- Kellam SG, Langevin DJ. A framework for understanding "evidence" in prevention research and programs. *Prevention Science*. 2003; 4:137–153. [PubMed: 12940466]
- Kumpfer KL, Alvarado R. Family-strengthening approaches for the prevention of youth problem behaviors. *American Psychologist*. 2003; 58:457–465. [PubMed: 12971192]
- Machado MP. Substance abuse treatment, what do we know? *The European Journal of Health Economics*. 2005; 6:53–64. [PubMed: 15703912]
- McCollister KE, French MT, Pyne JM, Booth B, Rapp R, Carr C. The cost of treating addiction from the client's perspective: Results from a multi-modality application of the client datcap. *Drug and Alcohol Dependence*. 2009; 104:241–248. [PubMed: 19574000]
- Miller, TR.; Hendrie, D. *Substance abuse prevention dollars and cents: A cost-benefit analysis*. Rockville, MD: Center for Substance Abuse Prevention, Substance Abuse and Mental Health Services Administration; 2008. (DHHS Pub. No. (SMA) 07-4298)
- Mitchel ME, Hu TW, McDonnell NS, Swisher JD. Cost-effectiveness analysis of an educational drug-abuse prevention program. *Journal of Drug Education*. 1984; 14:271–292. [PubMed: 6443126]

- Mojtabai R, Zivin JG. Effectiveness and cost-effectiveness of four treatment modalities for substance disorders: A propensity score analysis. *Health Services Research*. 2003; 38:233–259. [PubMed: 12650390]
- Mooney, CZ. Monte carlo simulation. Thousand Oaks, CA: Sage; 1997.
- NIDA. Report of the blue ribbon task force on health services research at the national institute on drug abuse. Bethesda, MD: National Institutes of Health; 2004.
- Pacileo G, Fattore G. Alcohol abuse prevention in young people: An economic simulation. *Journal of Substance Use*. 2009; 14:385–392.
- Pals SL, Murray DM, Alfano CM, Shadish WR, Hannan PJ, Baker WL. Individually randomized group treatment trials: A critical appraisal of frequently used design and analytic approaches. *American Journal of Public Health*. 2008; 98:1418–1424. [PubMed: 18556603]
- Costs, benefits, and cost-effectiveness of comprehensive drug abuse prevention. In: Pentz, MA., editor; Bukoski, WJ.; Evans, RI., editors. *Cost-benefit/cost-effectiveness research of drug abuse prevention: Implications for programming and policy*. Rockville, MD: National Institutes of Health; 1998. p. 111-129.
- Plotnick RD. Applying benefit-cost analysis to substance use prevention programs. *Substance Use & Misuse*. 1994; 29:339–359.
- Popovici I, French MT, McKay JR. Economic evaluation of continuing care interventions in the treatment of substance abuse recommendations for future research. *Evaluation Review*. 2008; 32:547–568. [PubMed: 18334678]
- Rhiannon TE, Cilleachair A, Bywater T, Hughes DA, Hutchings J, Scott. Parenting programme for parents of children at risk of developing conduct disorder: Cost effectiveness analysis. *British Medical Journal*. 2007; 334:682–685. [PubMed: 17350965]
- Royston P. Multiple imputation of missing values. *Stata Journal*. 2004; 4:227–241.
- Rubin, DB. Multiple imputation for nonresponse in surveys. New York: John Wiley & Sons; 1987.
- Ruger JP, Lazar CM. Economic evaluation of drug abuse treatment and hiv prevention programs in pregnant women: A systematic review. *Addictive Behaviors*. 2012; 37:1–10. [PubMed: 21962429]
- Rutten-van Molken MP, van Doorslaer EK, van Vliet RC. Statistical analysis of cost outcomes in a randomized controlled clinical trial. *Health Economics*. 1994; 3:333–345. [PubMed: 7827649]
- Salome HJ, French MT, Miller M, McLellan AT. Estimating the client costs of addiction treatment: First findings from the client drug abuse treatment cost analysis program (client datcap). *Drug and Alcohol Dependence*. 2003; 71:195–206. [PubMed: 12927658]
- Salome HJ, French MT, Scott C, Foss M, Dennis M. Investigating variation in the costs and benefits of addiction treatment: Econometric analysis of the chicago target cities project. *Evaluation and Program Planning*. 2003; 26:325–338.
- SAO. Mileage reimbursement rates for use of personal vehicles. 2009 from <http://www.georgialibraries.org/kb/files/Policy%20Document%20-%20Mileage%20Rates%2020090101.pdf>.
- Schafer JL, Graham JW. Missing data: Our view of the state of the art. *Psychological Methods*. 2002; 7:147–177. [PubMed: 12090408]
- Schori M. Valuation of drug abuse: A review of current methodologies and implications for policy making. *Research on Social Work Practice*. 2011; 21:421–431.
- Spoth R, Randall GK, Shin C, Redmond C. Randomized study of combined universal family and school preventive interventions: Patterns of long-term effects on initiation, regular use, and weekly drunkenness. *Psychology of Addictive Behaviors*. 2005; 19:372–381. [PubMed: 16366809]
- Spoth RL, Gyll M, Day SX. Universal family-focused interventions in alcohol-use disorder prevention: Cost-effectiveness and cost-benefit analyses of two interventions. *Journal of Studies on Alcohol*. 2002; 63:219–228. [PubMed: 12033699]
- StataCorp. Stata statistical software: Release 12. College Station, TX: Stata Corp LP; 2011.
- Sterne JAC, White IR, Carlin JB, Spratt M, Royston P, Kenward MG, Wood AM, Carpenter JR. Multiple imputation for missing data in epidemiological and clinical research: Potential and pitfalls. *British Medical Journal*. 2009; 339:157–160.

- The costs, cost-effectiveness, and cost-benefit of school and community counseling services. In: Swisher, JD., editor; Locke, DC.; Myers, JE.; Herr, EL., editors. The handbook of counseling. Thousand Oaks, CA: Sage Publications, Inc.; 2001. p. 669-680.
- Swisher JD, Scherer J, Yin RK. Cost-benefit estimates in prevention research. *The Journal of Primary Prevention*. 2004; 25:137–148.
- Thompson KM, Graham JD. Going beyond the single number: Using probabilistic risk assessment to improve risk management. *Human and Ecological Risk Assessment*. 1996; 2:1008–1034.
- Tricker R, Davis LG. Implementing drug education in schools: An analysis of the costs and teacher perceptions. *Journal of School Health*. 1988; 58:181–185. [PubMed: 3386197]
- Weinstein MC, O'Brien B, Hornberger J. Principles of good practice of decision analytic modeling in health care evaluation: Report of the ispor task force on good research practices-modeling studies. *Value in Health*. 2003; 6:9–17. [PubMed: 12535234]
- Woodward AM, Raskin IE, Blacklow B. A profile of the substance abuse treatment industry: Organization, costs, and treatment completion. *Substance Use & Misuse*. 2008; 42:647–679. [PubMed: 18393082]
- Zarkin GA, Dunlap LJ, Homs G. The substance abuse services cost analysis program (sascap): A new method for estimating drug treatment services costs. *Evaluation and Program Planning*. 2004; 27:35–43.

Demographic characteristics of SAAF-T and ACI participants. The p-value is based on the Student's t-test for the "Means" categories, the proportion test for gender and caregiver employment and the Wilcoxon rank sum test for caregiver education and housing status.

Table 1

Demographic Category	SAAF-T	ACI	All	p-value
N	102	97	199	n/a
Gender				
Caregiver, Female %	0.94	0.99	0.96	0.063
Teen, Female %	0.60	0.67	0.63	0.333
Means				
Caregiver Age	42.6	43.3	43.0	0.548
Teen Age	16.0	16.0	16.0	0.733
Household Income	\$24 502	\$20 890	\$22 728	0.256
Household Size	5.0	4.7	4.9	0.556
Caregiver Education				
Less than HS Degree	28	19	47	
HS Degree, Less than Bachelor's Degree	60	67	127	
Bachelor's Degree or higher	12	10	22	0.413
Housing Status				
Own Home	55	49	104	
Rent	38	30	68	
Public Housing	3	4	7	
Other	4	13	17	0.242

Table 2

Summary of the mean costs for categories included in this analysis. For a cost category that includes both a SAAF-T and ACI total, there is a difference expected between the two interventions.

Cost Category	SAAF-T	ACI	Combined
Personnel Time	4318	3655	
Facilitators - Home Engagement			268
Facilitators - Intervention	2270	1746	
CFR Administrative Staff	1601	1433	
Prevention Supervisors	179	208	
Site & Ancillary Services	2814	2791	
Site Rent			780
Catering			1484
Childcare	161	138	
Participant Transportation			262
Site Assistant			127
Supplies & Equipment	718	694	
Supplies/Gifts	361	358	
Equipment	166	145	
Postage			191
Transportation	1764	1764	
Personnel Time Traveling (non-reimbursed) [†]			692
Cost of Traveling/Reimbursements to Personnel			1072
Overhead	563	504	
Training	2997	1291	
Home Engagement Training			305
Intervention Training	2577	871	
Debriefing			115
Participant Time at Intervention[†]	2236	1914	

[†] Cost category not included in the provider perspective.

Cost estimates for both the MI and PSA methods, including the mean, standard error (SE) and 95 percent confidence interval (95% CI) for the total programmatic costs and incremental difference between SAAF-T and ACI. MI method results are based on 20 imputation datasets and application of Rubin's rules (Rubin, 1987) to determine the standard error. PSA method results are based on 10,000 simulations of the model using collected costs as a distribution for each key input parameter. All estimates are in units of 2009 US dollars.

Table 3

	SAAF-T			ACI			SAAF-T - ACI		
	Mean	SE	95% CI	Mean	SE	95% CI	Mean	SE	95% CI
Societal Perspective									
MI Method									
All Categories	16 251	577	(14 792, 17 710)	14 102	389	(13 119, 15 085)	2149	693	(397, 3901)
PSA Method									
Random Selection	16 405	1318	(13 871, 19 082)	13 854	1151	(11 689, 16 210)	2552	1760	(-949, 6033)
Bootstrap Selection	16 419	740	(14 987, 17 884)	13 836	549	(12 768, 14 924)	2583	913	(778, 4346)
Provider Perspective									
MI Method									
All Categories	13 478	331	(12 641, 14 316)	11 531	328	(10 701, 12 360)	1948	463	(777, 3118)
PSA Method									
Random Selection	12 950	1127	(10 889, 15 319)	10 566	931	(8939, 12 603)	2385	1471	(-572, 5220)
Bootstrap Selection	12 965	515	(11 931, 13 935)	10 558	232	(10 114, 11 024)	2407	566	(1258, 3476)