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Electronic Supplementary Material 1

Methodological Details

This methodological appendix further describes technical details regarding the estimation of youth suicide rate for small areas, the implementation of the propensity score subclassification, and the estimation of the cost for each training.

Youth Suicide Rate by County, 1999-2014

While a leading cause of death among youths, suicides are relatively rare events. Even when combining several years of information, estimates of the youth suicide rate for small counties can be extremely unreliable. We used a 2-step procedure to obtain reliable estimates of youth suicide rate for small areas. Firstly, we combined very small counties into areas with at least 5,000 youths. Secondly, we resorted to model-based small area estimation (SAE).

In essence, a model-based SAE combines information from a direct estimate and an estimate based on a regression using auxiliary variables. The direct estimate takes precedence when the county is sufficiently large while the regression estimate is weighted more heavily when the former becomes unreliable. Through the regression, the model-based estimate for an area borrows strength from related areas.

Implementation. We grouped counties with fewer than 5,000 youths aged 10 to 24 (on average during 1999-2014) with contiguous counties using the regionalization algorithm developed by Assuncao and colleagues (Assuncoa, Neves, Camara & Freitas, 2006).[a] In addition to ensuring contiguity and the required minimum size, the procedure minimized within-area

[a] Implemented in the function ‘skater’ in R’s ‘spdep’ package (Bivand & Piras, 2015).

differences in other characteristics, including, race-ethnic composition, rurality, median income, poverty, health insurance coverage, and unemployment rate.

Once the areas with the minimum number of youths were created, we used the Fay-Herriot model to obtain model-based estimates (Fay & Herriot, 1979). We took advantage of the implementation of this model in the SAE package (Molina & Marhuenda, 2015). Extension of this model to the case of (unexplained) spatial correlation among data from neighboring areas was also explored, but they resulted in a virtually identical fit.

We used a log transformation of the response variable (to increase normality and reduce the dependence of variance on the mean). The final model included the following predictors (average value during the period): percentage of American Indian/Alaskan Native, African American, Asian/Pacific Islander and Hispanic individuals, percentage females (CDC WONDER, 2015a), percentage with no health insurance (U.S. Census Bureau, 2016), median household income (U.S. Census Bureau, 2015), unemployment rate (Bureau of Labor Statistics, 2015), rurality 6 level classification (CDC WONDER, 2015b). Importantly, the model included overall suicide rates (youths and adults) and youth mortality by any cause (suicide and non-suicide) as well as state-level youth suicide rates. These predictors are estimated from the same source as the area's youth suicide mortality (CDC WONDER, 2015b) but with far greater precision.

We then used a stepwise procedure to select these predictors from a larger set that also included poverty rate. The final model also included 5 second-order polynomial terms and 9 two-way interactions, which similarly selected based on a stepwise procedure (from the entire list of possible second-order polynomial terms and two-way interactions). The final model fitted the data very well (adjusted $R^2 = 74.2$). All the procedures were implemented using the R environment (R Core Team, 2016).

Results. Direct estimates of youth suicide rate were unreliable for 60 of the counties (coefficient of variation [CV] greater than 30), and had relatively good reliability for only 12 of the counties (CV < 15). Starting with 3,142 counties, a total of 1,806 areas with at least 5,000 youths were created by combining small counties with contiguous counties with similar sociodemographic characteristics. Even after this grouping, a direct estimate of the youth suicide rates was still unreliable for 38 of the areas (CV > 30), and had relatively good reliability for only 19 of the areas (CV < 15). Model-based estimates, however, achieved relatively high reliability: the CV for the model-based SAE estimates was lower than 15 for all areas.

Subclassification on the Propensity Score

To ensure that participants in either training are similar on all the covariates considered before engaging in any comparison of outcomes we utilized subclassification on the propensity score (also called stratification or interval matching) originally proposed by Roseumbun and Rubin (Rosenbaum & Rubin, 1983; 1984).

Propensity model. Using logistic regression, we estimated the propensity to participate in a brief training rather than an in-depth training as a function of a set of individual and contextual covariates. The final specification of the logistic regression model was aided by a stepwise procedure. Specifically, starting with a model that includes only the main effect for all the individual level and contextual covariates, a stepwise procedure was used to determine whether any 2-way interaction and/or second order polynomial term for continuous covariates increased model fit. Higher order interactions or polynomial terms were not considered.

Trimming. Individuals receiving 1 training who had hardly any comparable counterpart receiving the alternative training were excluded from the analysis. We identified these cases based on the extremely low or high estimated propensity score. Propensities higher than .9 or lower than .1 were used as thresholds. This approximate rule was suggested by Crump and colleagues (2009). The goal of this exclusion was to focus estimation and inference in the sample of brief training and in-depth training participants whose characteristics actually overlap. Once the final sample was selected in this way, we estimated the propensity score once more.

Subclassification. In order to identify subclasses or strata with similar propensities, we initially used the quartiles of the distribution of the estimated propensity score based on work from Cochran (1968) showing this choice removed much of the bias. Because of significant variation in propensity scores across subclasses using the Cochran method, we implemented instead the algorithm proposed by Imbens and Rubin (2015). We started by dividing the sample into 2 subclasses using the median propensity value. We computed a t statistic for the difference in mean propensity score between participants in either training in each of the 2 subclasses. If the t statistic was larger than 1.96 in any subclass, we further split the sample in that subclass, using again the median propensity value within that subclass. We continued splitting in this way until no t statistic was larger than the threshold. The algorithm was also stopped if further splitting would have resulted in a subclass with fewer than 30 cases or fewer than 5 participants in either training within the subclass.

Estimation. The analysis proceeds separately for each subclass within each setting as if the information in that subclass had arisen from a randomized trial. Within each subclass, the comparison between outcomes of in-depth and brief trainees was performed using linear regression with standard errors robust to heteroscedasticity and clustering within grantees. The regression included linear terms for each of the covariates used previously in the subclassification. The adjustment has the purpose of increasing the precision of the estimates of the difference in outcomes as well as removing any residual mismatch in covariates.

Setting-wise results are weighted averages of the respective subclass results using the size of the subclass in the sample to determine the weights. Overall cross-setting results (Table 3) are similarly obtained as weighted averages. The distribution of trainees by setting in that case were based on the TASP, which unlike the TUP-S constitutes a census. To the extent that all relevant differences between participants were taken into account, the estimated difference in outcomes can be interpreted as the average treatment effect, the difference between the observed outcome and the outcome that would have been observed had the participant received the alternative training.

Cost Estimation

Table 3a presents a detailed table of the components included in the cost estimation for each training. The participants' opportunity cost is the main component (between 51 and 77 of the total cost depending on the setting and type of training) and reflects the substantial difference in the training length. To estimate the opportunity cost in each setting, we used hourly wage among individuals with occupation that most closely resembled the subclasses of trainees that were found to benefit the most from the in-depth training. The cost estimation does not include instructor (re)certification. We attempted to reflect the differential availability of trainers by decreasing the instructor travel cost for brief training trainers. For all components of the cost, national averages are used, and the actual cost in a particular locality may differ markedly from the average.

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Table 3a. Detailed Assumptions and Sources for the Cost of Brief and In-Depth Training[a]

Component	Brief	In-depth	Assumptions and Sources
Duration of the Training (Hours)	1.5	15	Average duration of GLS sponsored training events included in the sample based on TASP form, GLS National Outcome Evaluation.
Number of Participants	26	20	Average number of adults in GLS sponsored training events included in the sample based on TASP form, GLS National Outcome Evaluation.
Participants			
Opportunity Cost			
K-12	$57.50	$575.10	Based on the average of hourly wages between secondary school teachers of $28.90 and social workers of $23.90 plus 'fringe' among civilian workers in education and health services of 31.2.[c, d]
MH	$74.40	$744.30	Based on hourly wages among registered nurses of $34.10 plus 'fringe' among civilian workers in education and health services of 31.2.[c, d]
CS	$35.30	$353.40	Based on estimated cost of volunteer work per hour of $23.60.[e]
Travel	$11.50	$23.00	Based on IRS mileage rate $0.58 per mile for FY 2015.[f] Trainings are assumed to be conducted locally and require 20 miles of travel per day on average.
Per Diem	$0.00	$52.00	In the case of ASIST, 2-day meal and incidental per diem in a low-cost locality.
Instructor			
Opportunity Cost			
K-12	$2.20	$28.80	Same as participants.
MH	$2.90	$37.20	Same as participants.
CS	$1.40	$17.70	Same as participants.
			For ASIST, based on average itinerary fare for domestic flights of $377 in 2015.[g] For QPR half of that cost, to reflect greater availability of QPR trainers, is expected.
Travel	$7.30	$18.90	
Per Diem	$6.60	$17.20	Per diem in a low-cost locality for 1 and 2 days, respectively.[f]
Facility	$4.60	$39.60	Based on average half-day rate ($119) and 2 full-day rate ($396) in a sample of 47 facilities where GLS trainings were conducted.
Materials	$2.00	$36.00	Suicide Prevention Resource Center[b]

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Component	Brief	In-depth	Assumptions and Sources
Total Cost			
K-12	$91.70	$790.60	
MH	$109.20	$968.20	
CS	$68.60	$557.70	

[a]All costs are expressed in US$2015 per participant.

[b]Suicide Prevention Resource Center, 2013

[c]Bureau of Labor Statistics, 2016a

[d]Bureau of Labor Statistics, 2016b

[e]Independent Sector, 2016

[f]Internal Revenue Service, 2015

[g]Bureau of Transportation Statistics, 2016

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