Promoting Physical Activity in High Poverty Neighborhoods

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Data analyses

We first conducted descriptive analyses of park characteristics, park baseline observation data, and characteristics of resident survey respondents. To obtain community level population data we used census data and GIS methods to calculate population density and socio-demographic characteristics of the population within a one-mile radius of each park (USCensus, 2010a, 2010b). We calculated the violent crime rate in the park neighborhoods (1-mile radius around the study parks) using a City of Los Angeles Police Department publicly available dataset (DataLA, 2016). We also summarized process measures for the intervention by study arms. We then conducted formal statistical analyses of park use outcomes and survey data. The primary pre-specified outcome was estimated energy expenditure in parks from the SOPARC observations using MET scores, the ratio of work metabolic rate to standard resting metabolic rate. We assigned MET levels of 1.5 for sedentary, 3 for moderate, and 6 for vigorous activity as identified by Ainsworth et al (Ainsworth et al., 2000). The secondary outcome measure was the number of observed park users. Survey outcomes included self-reported park use (number of visits in past seven days, duration of park visits, awareness of park programs, having participated in park programs), perception of park safety, and number of weekly exercise sessions.

We fitted difference-in-differences (DID) models between the two measurement waves and four study arms (Yang & Tsiatis, 2001). The effect of the intervention was modeled as the wave by study arm interaction. All models used random effects to account for intra-class correlation within each park as well as fixed effects to account for observation times (time of day, weekend versus weekdays). This approach can eliminate temporal trends unrelated to the intervention and is particularly suitable for this study due to the relatively long observation periods. We also included indicators for park cohorts to account for potential seasonal effects.

We used negative binomial distributions in the DID models due to the sizable heteroscedasticity in park use outcomes (Cohen et al., 2012). Effects of the intervention were presented in the scale of multiplicative scale (i.e., % changes) in these models. We also examined the outcomes by two age groups (youths versus adults). In analyzing survey outcomes, we controlled for respondent-level covariates to reduce estimation biases because randomization was not at the individual level, including gender, age, education level, obesity status, address buffer (<.25 mile, .25 to .5 miles, and .5 miles to 1 mile to park), self-rated health, perception of park safety, primary language, and having children under 18 years old. All statistical models were fitted in SAS 9.4. We also conducted sensitivity analyses using robust standard errors for park clustering effects and alternative scale for transformed mean outcomes (log or logit) wherever appropriate. The main findings were not sensitive to alternative model specifications.

Statistical power: This study was powered to detect a small to medium standard effect size under the regular setting of two-sided p-value<0.05 and power>0.80. With 12 parks in each study arm and the extensive repeated measurements in each park (18 hourly observation per wave for two waves), we can detect a difference of 0.34 times standard deviation (SD) between any two arms when the intra-class correlation is no greater than 0.10. Based on historic data from previous studies (average park use 55 persons/hour, SD=35, approximately)(Cohen et al., 2013) meant that we could detect an additional 11.9 persons/hour. Because most survey outcomes were categorical, we used a two-sample z-test for calculating the detectable effect size for survey analysis. With 20 surveys in each wave and in each park's neighborhood, we could detect a difference of 15 percentage points for a binary outcome with a baseline prevalence between 20% and 80%. The detectable effect size is even smaller if the baseline prevalence rate is very high or very low (e.g. <20%, or >80%).