Journal of School Psychology 52 (2014) 213–230

Contents lists available at ScienceDirect

Journal of School Psychology

journal homepage: www.elsevier.com/locate/jschpsyc

An effect size measure and Bayesian analysis of single-case designs

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ARTICLE INFO

Article history:
Received 2 September 2013
Received in revised form 12 December 2013
Accepted 14 December 2013
Available online 16 January 2014

Keywords:
Standardized effect size
Autocorrelation
Bayesian analysis

ABSTRACT

This article describes a linear modeling approach for the analysis of single-case designs (SCDs). Effect size measures in SCDs have been defined and studied for the situation where there is a level change without a time trend. However, when there are level and trend changes, effect size measures are either defined in terms of changes in R^2 or defined separately for changes in slopes and intercept coefficients. We propose an alternate effect size measure that takes into account changes in slopes and intercepts in the presence of serial dependence and provides an integrated procedure for the analysis of SCDs through estimation and inference based directly on the effect size measure. A Bayesian procedure is described to analyze the data and draw inferences in SCDs. A multilevel model that is appropriate when several subjects are available is integrated into the Bayesian procedure to provide a standardized effect size measure comparable to effect size measures in a between-subjects design. The applicability of the Bayesian approach for the analysis of SCDs is demonstrated through an example.
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1. Introduction

Random assignment of experimental units to treatment and control groups, a concept introduced by Sir Ronald Fisher, revolutionized experimental research by enabling direct causal inference. It has become the standard research design by which the effectiveness of a treatment or an experimental manipulation is assessed. In their highly influential work, Campbell and Stanley (1966) termed such experiments “true experiments” while labeling experiments without random assignment as “quasi-experiments”. However, there are many situations where random assignment of units to experimental and control conditions is neither feasible nor desirable. Recognizing this, Campbell and Stanley devoted considerable effort to explicating the threats to causal inference (internal validity) of a variety of quasi-experimental designs. One of the quasi-experimental designs described by Campbell and Stanley that provides control for most of the threats to internal validity is the interrupted time series design, where an entity (subject, case, organization) is measured repeatedly before and after the introduction of an intervention. By analyzing the change in the pattern of data before and after the intervention in such interrupted time series, it is possible to establish a causal link between the intervention and the change observed (Shadish, Cook, & Campbell, 2002). It is interesting to note that such time series designs were employed by scientists to study natural phenomena such as the occurrence of sunspots and by economists to study market behavior long before these designs became known to social and behavioral scientists.

Although statistical analysis of time series data has a long history dating back to the 1920s and has been the main tool of economic forecasting, modern applied time series analysis can arguably be traced to the Box and Jenkins (1970) approach for the analysis of time series data. The increasing emphasis on the evaluation of social and education programs at that time stimulated

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ACTION EDITOR: William Shadish

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http://dx.doi.org/10.1016/j.jsp.2013.12.002

interest in time series analysis among applied researchers. Glass, Willson, and Gottman (1975) proposed the use of quasi-experimental time series designs using the Box and Jenkins Autoregressive Integrated Moving Average (ARIMA) models to evaluate such programs. Since the ARIMA models were designed to handle observations made over time on a single unit, applying the ARIMA models to evaluate, for example, the performance of a group of children after the introduction of a new approach required collapsing the data to a single value (the mean) at each time point. Swaminathan and Algina (1977) argued against collapsing the data in such situations and developed a proper multivariate linear model procedure for the analysis of interrupted time series data that, unlike the ARIMA models, allowed for a general covariance structure for the dependence among the observations over time. Simonton (1977) proposed a univariate regression model-based procedure with a restricted first-order autoregressive covariance structure, a procedure that was criticized by Algina and Swaminathan (1979) for its lack of statistical efficiency by not using the available information in the data. Velicer and Molenaar (2013) have reviewed time series analysis procedures and described a variety of models for the analysis of interrupted time series data.

Single case designs (SCDs) are interrupted time series designs, and can provide a scientifically rigorous approach for documenting causal effects (see for example, Hersen & Barlow, 1976; Kazdin, 1982; Kennedy, 2005; Kratochwill & Levin, 1992; Kratochwill & Stoiber, 2000; Odom et al., 2005; Todman & Dugard, 2001; Whitehurst, 2003). Although numerous descriptive procedures based on visual analysis have been developed for the analysis of SCD data, the statistical procedures for the analysis of SCDs have been criticized either as being too difficult for researchers or for their inability to take into account such realities as serial dependence and trend in the data. The primary challenge posed by SCDs is that they are typically based on only a few time points, rendering the ARIMA models impractical and the Swaminathan–Algina multivariate approach inappropriate. Univariate linear model-based approaches for analyzing SCDs have been proposed by such researchers as Allison and Gorman (1993), Center, Skiba, and Casey (1985–1986), Gorsuch (1983), and White, Rusch, Kazdin, and Hartmann (1989). Excellent reviews of these procedures are provided by Brossart, Parker, Olson, and Mahadevan (2006) and Manolov and Solanas (2013).

In any data collection and modeling procedure that involves obtaining repeated measurements on subjects, the fact that the observations are not independent must be addressed in developing a model and the attendant estimation procedure. Although the presence of serial dependence in SCDs has been questioned by some (Huitema, 1985), most researchers agree that serial dependence must be taken into account in modeling SCD data. It is not possible, however, to model the dependence among the observations using an unrestricted variance–covariance matrix (as in the Swaminathan–Algina procedure), as many subjects are needed at each time point to estimate a general variance–covariance matrix. One solution to this problem is to assume that the dependence among the observations arises through an underlying process (i.e., assume that the dependence among the observations is governed by an autoregressive or moving average process or a combination of both). Again, as mentioned earlier, identifying the proper model requires more observations than is feasible in SCDs. In order to avoid the tedious process of model identification, Velicer and McDonald (1984, 1991) suggested the use of a fifth-order autoregressive model, an approach that may not be realistic in short time series with few observations. Harrop and Velicer (1985) and Velicer and Molenaar (2012) found that a first-order autoregressive model generally works well. Hedges, Pustejovsky, and Shadish (2012, 2013) employed a first-order autoregressive model in developing a *d*-Type effect size estimator. Following these authors, we shall model serial dependence among the observations using a first-order autoregressive process.

The second issue that must be addressed is that of an effect size measure suitable for SCDs. Hedges (2007) and Hedges et al. (2012) provided an extensive discussion of effect size issues. Horner, Swaminathan, Sugai, and Smolkowski (2012) argued that strategies for measuring effect size must be in place in order for results from SCDs to be taken seriously. Although there are numerous approaches for assessing effect size in single-case research (Parker, Hagan-Burke, & Vannest, 2007), each of the available approaches carries important shortcomings (Maggin et al., 2011). Appropriate linear model-based effect size measures have been proposed, but these are valid for the situation where there is level change without a trend (zero slopes) or a common trend (equal slopes) with level change. For the situation where there are both level and slope changes, Van den Noortgate and Onghena (2003) and Beretvas and Chung (2008a,b) recommended two effect size measures, one for level change and one for slope change, arguing that these two effect sizes are more informative than an overall R^2 based effect size measure that combines the two. As level change in the presence of slope change is not the same at different points on the time continuum, these authors centered the time variable at the point of intervention to provide a measure of the change in the level at this point. The change in level may increase or decrease as time progresses, however, and as a result, reporting the level change and slope change parameters separately will not necessarily capture the overall effect of the intervention. A measure that combines slope change and level change parameters will capture the overall effect and has been recommended by several researchers. Following a suggestion by Rubin (1977), Rogosa (1980) proposed that the treatment effect in analysis of covariance be defined as the average of the differences in predicted values between experimental groups across the values of the concomitant variable when the regression lines are not parallel. In the context of evaluation research, Bloom (1999) employed a similar approach, averaging the post-intervention deviations from the baseline trend to document the overall impact of an intervention. More recently, such a measure was used effectively in a study to evaluate the "total impact" of the No Child Left Behind policy on reading achievement (Wong, Cook, & Steiner, 2011). Wong, Wing, Steiner, Wong, and Cook (2012) recommended a measure that combines slopes and intercepts in program evaluation. Gorsuch (1983) and Allison and Gorman (1993) have suggested comparing the predicted values at the end of the intervention phase to assess the intervention effect in SCD research.

Given the issues that remain in the analysis of SCDs, the purposes of this article are to describe (a) a linear model that takes into account serial dependence in SCD data, (b) an effect size measure that combines level and slope change, and (c) a Bayesian procedure for the analysis of SCD data. An example of SCD analysis using the Bayesian approach is provided.

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