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Research Dialogue

Median splits, Type II errors, and false–positive consumer psychology: Don't fight the power

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Abstract

Considerable prior statistical work has criticized replacing a continuously measured variable in a general linear model with a dichotomy based on a median split of that variable. Iacobucci, Posovac, Kardes, Schneider, and Popovich (2015-in this issue) defend the practice of "median splits" using both conceptual arguments and simulations. We dispute their conceptual arguments, and we have identified technical errors in their simulations that dramatically change the conclusions that follow from those simulations. We show that there are no real benefits to median splits, and there are real costs in increases in Type II errors through loss of power and increases in Type I errors through false–positive consumer psychology. We conclude that median splits remain a bad idea.

Keywords: Median splits; Statistical power; False–positive psychology

Introduction

Researchers can make Type I or Type II errors, rejecting a true null hypothesis, or failing to reject a false null hypothesis. In the same way, journals can make two kinds of errors, rejecting a paper that is later concluded to be insightful or publishing a paper that is later concluded not to be true. For instance, Gans and Shepherd (1994) reviewed famous economics papers that were rejected multiple times before being published and regarded as great. George Akerlof's (1970) "A Market for Lemons" paper was rejected by the *American Economic Review*, the *Journal of Political Economy*, and the *Review of Economic Studies*. Two said it was trivial, the other that it was too general to be true. Those journals made a Type II error. Ackerlof later won the Nobel Prize in economics for the work. In other cases, a prestigious journal publishes a sensational result that seems too good to be true and is later discredited, reflecting a Type I error. Prominent examples are cold fusion claims by Fleischmann and Pons (1989) and Bem's (2011) finding of correct prediction of events in the future (i.e. ESP). Both were followed by numerous failures to replicate, and in the case of Bem, detailed critiques of the statistical analysis by the editor who had accepted the original paper (Judd, Westfall, & Kenny, 2012).

The paper by Iacobucci, Posovac, Kardes, Schneider, and Popovich (2015- in this issue, hereafter IPKSP) may fall within the latter category. These authors make conceptual arguments and present statistical simulations about the consequences of median splits of continuous independent variables in linear models. Later

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in this commentary, we point out technical errors in their statistical simulations. The actual programming code in Appendix A of IPKSP does not match the description in the text of their paper, and the result is that the simulations do not support the conclusions IPKSP wish to draw. Consequently, the bulk of the contribution of their paper must stand or fall on their conceptual arguments for the appropriateness of median splits, which we argue are often misguided. We first evaluate their conceptual arguments and present conceptual arguments of our own, then present our reanalysis and interpretation of their simulation results.

The topic of categorizing continuous predictor variables by splitting them at their median has been covered extensively, including in our own papers (e.g., Cohen, 1983; DeCoster, Iselin, & Gallucci, 2009; Fitzsimons, 2008; Humphreys, 1978; Humphreys & Fleishman, 1974; Irwin & McClelland, 2003; MacCallum, Zhang, Preacher, & Rucker, 2002; Maxwell & Delaney, 1993). We know of no statistical argument in favor of median splits to counterbalance the chorus of statistical critiques against them. Because there is a danger that IPKSP may convince researchers to use median splits, we briefly present the arguments against their claims.

Our commentary will proceed as follows. First we will very briefly present the core statistical reasons why median splits are to be avoided. Second, we will review nonstatistical justifications for median splits presented by IPKSP—including the argument that median splits are "conservative"—and will show that there are ready answers for those justifications. Then we will discuss in more depth the statistical considerations for when median splits affect Type II errors, adversely affecting power. In our view, power is the most compelling reason to avoid median splits. We will address the conservatism defense in that section, where we will show that steps that lower the power of reports of significant findings in a journal increase the percent of published results that are Type I errors. Finally, we will address the discrepancies between the actual programming code in IPKSP's Appendix A and the descriptions in the body of IPKSP's paper and show how those discrepancies invalidate the conclusions drawn by IPKSP.

The statistical case against median splits in a nutshell

We highlight the statistical case against median splits in a simple design with a dependent variable Y and a single measured independent variable X. We later consider multiple independent variables in our reanalysis of IPKSP's simulations. Assume X is an indicator of some latent construct and that the observed X is linearly related to the underlying construct. By splitting the measured X at its median, one replaces X with a categorical variable X′ (e.g., 1 = greater than median, 0 = less than or equal to the median). There are four main consequences of this substitution, discussed in detail below:

a. This substitution introduces random error in the measure of the latent construct and all of the problems that adding error brings.
b. The analysis now is insensitive to the pattern of local covariation between X and Y within groups defined by the median split. All that matters is the mean difference.
c. This analysis involves a nonlinear transformation of the original X to a step function of the original X on the dependent variable Y. The use of a median split on X makes it impossible to test a substantive theoretical claim of a step function relation of latent X to dependent variable Y.
d. If one believes that there is a step function relation of latent X to the dependent variable Y, the threshold of that function is presumably general and not sample-dependent. A median split is sample-dependent.

a. Errors in variables

Introducing random error has two interrelated negative consequences. First, when there is a nonzero population correlation between X and Y, the correlation between the median split X′ and Y will be lower in expectation, though adding error can make the correlation higher in a subset of samples. Also, splitting at the median makes the measure of the latent construct underlying X noisier. Expected effect size goes down, and statistical power is a function of effect size.

Adding random error to one's measure of X creates "errors in variables" in regression models, a source of bias in estimated (standardized) coefficients. Since multiple regression models assume errorless measurement of the latent constructs underlying X, adding error via median split creates inconsistent estimates of the standardized coefficient (i.e., estimates that do not have expected value equal to the true parameter). We will demonstrate that this practice is hazardous, not "conservative" as IPKSP maintain. It is surprising to us that Iacobucci, Saldanha, and Deng (2007) have argued so eloquently about the negative consequences of ignoring errors in variables in statistical mediation analysis, but in the current paper IPKSP defend the deliberate adding of measurement error to an independent variable.

b. Ignoring information about local within-group covariation between X and Y

Consider a simple regression of Y on continuously measured X, and a reanalysis of the same data replacing X with X′ defined by a median split. The analysis using median splits is insensitive to the pattern of local covariation between Y and the continuous X within the above-median and below-median groups. The analysis using the continuously measured X is sensitive to that within-group covariation. As a thought experiment, imagine holding constant the univariate distributions of X and Y above and below the median, but scrambling the pairings of X and Y within the subsets of points above and below the median. Different scrambles produce widely different slopes of the regression of Y on continuous X, some significant, some not, but identical slopes of the regression of Y on X′. Thus, it is untrue that it is uniformly conservative to use the median split. In some cases the *t* statistics from the median split can be more significant than the *t* statistics from regressing Y on continuous X, and in most cases less significant. Such inconsistencies could allow unscrupulous researchers to pick whichever outcome was more favorable, as we discuss in more detail later.