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## References

**Barnard et al.: Nonparametric standard errors and confidence intervals: Discussion**

**Barnard-Collins-Farewell-et-al-1981**

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George A. Barnard et al. “Nonparametric standard errors and confidence intervals: Discussion”. In: *The Canadian Journal of Statistics / La Revue Canadienne de Statistique* 9.2 (1981), pp. 158–170. DOI: [10.2307/3314609](https://doi.org/10.2307/3314609).

**Baron et al.: The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations** **Baron-Kenny-1986**

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Reuben M. Baron and David A. Kenny. “The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations”. In: *Journal of Personality and Social Psychology* 51.6 (1986), pp. 1173–1182. DOI: [10.1037/0022-3514.51.6.1173](https://doi.org/10.1037/0022-3514.51.6.1173).

Abstract: In this article, we attempt to distinguish between the properties of moderator and mediator variables at a number of levels. First, we seek to make theorists and researchers aware of the importance of not using the terms moderator and mediator interchangeably by carefully elaborating, both conceptually and strategically, the many ways in which moderators and mediators differ. We then go beyond this largely pedagogical function and delineate the conceptual and strategic implications of making use of such distinctions with regard to a wide range of phenomena, including control and stress, attitudes, and personality traits. We also provide a specific compendium of analytic procedures appropriate for making the most effective use of the moderator and mediator distinction, both separately and in terms of a broader causal system that includes both moderators and mediators.

**Browne: Asymptotically distribution-free methods for the analysis of covariance structures** **Browne-1984**

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Michael W. Browne. “Asymptotically distribution-free methods for the analysis of covariance structures”. In: *British Journal of Mathematical and Statistical Psychology* 37.1 (May 1984), pp. 62–83. DOI: [10.1111/j.2044-8317.1984.tb00789.x](https://doi.org/10.1111/j.2044-8317.1984.tb00789.x).

Abstract: Methods for obtaining tests of fit of structural models for covariance matrices and estimator standard error which are asymptotically distribution free are derived. Modifications to standard normal theory tests and standard errors which make them applicable to the wider class of elliptical distributions are provided. A random sampling experiment to investigate some of the proposed methods is described.

**Chesher et al.: The bias of a heteroskedasticity consistent covariance matrix estimator** **Chesher-Jewitt-1987**

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Andrew Chesher and Ian Jewitt. “The bias of a heteroskedasticity consistent covariance matrix estimator”. In: *Econometrica* 55.5 (Sept. 1987), p. 1217. DOI: [10.2307/1911269](https://doi.org/10.2307/1911269).

**Cloninger: Neurogenetic adaptive mechanisms in alcoholism** **Cloninger-1987**

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C. Robert Cloninger. “Neurogenetic adaptive mechanisms in alcoholism”. In: *Science* 236.4800 (Apr. 1987), pp. 410–416. ISSN: 1095-9203. DOI: [10.1126/science.2882604](https://doi.org/10.1126/science.2882604).

Abstract: Clinical, genetic, and neuropsychopharmacological studies of developmental factors in alcoholism are providing a better understanding of the neurobiological bases of personality and learning. Studies of the adopted-away children of alcoholics show that the predisposition to initiate alcohol-seeking behavior is genetically different from susceptibility to loss of control after drinking begins. Alcohol-seeking behavior is a special case of exploratory appetitive behavior and involves different neurogenetic processes than do susceptibility to behavioral tolerance and dependence on

the antianxiety or sedative effects of alcohol. Three dimensions of personality have been described that may reflect individual differences in brain systems modulating the activation, maintenance, and inhibition of behavioral responses to the effects of alcohol and other environmental stimuli. These personality traits distinguish alcoholics with different patterns of behavioral, neurophysiological, and neuropharmacological responses to alcohol.

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**Cox et al.: A motivational model of alcohol use****Cox-Klinger-1988**

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W. Miles Cox and Eric Klinger. “A motivational model of alcohol use”. In: *Journal of Abnormal Psychology* 97.2 (May 1988), pp. 168–180. ISSN: 0021-843X. DOI: [10.1037/0021-843x.97.2.168](https://doi.org/10.1037/0021-843x.97.2.168).

Abstract: The final, common pathway to alcohol use is motivational. A person decides consciously or unconsciously to consume or not to consume any particular drink of alcohol according to whether or not he or she expects that the positive affective consequences of drinking will outweigh those of not drinking. Various factors (e.g., past experiences with drinking, current life situation) help to form expectations of affective change from drinking, these factors always modulated by a person’s neurochemical reactivity to alcohol. Such major influences include the person’s current nonchemical incentives and the prospect of acquiring new positive incentives and removing current negative incentives. Our motivational counseling technique uses nonchemical goals and incentives to help the alcoholic develop a satisfying life without the necessity of alcohol. The technique first assesses the alcoholic’s motivational structure and then seeks to modify it through a multicomponent counseling procedure. The counseling technique is one example of the heuristic value of the motivational model.

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**Efron: Nonparametric standard errors and confidence intervals****Efron-1981a**

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Bradley Efron. “Nonparametric standard errors and confidence intervals”. In: *Canadian Journal of Statistics / La Revue Canadienne de Statistique* 9.2 (1981), pp. 139–158. DOI: [10.2307/3314608](https://doi.org/10.2307/3314608).

Abstract: We investigate several nonparametric methods; the bootstrap, the jackknife, the delta method, and other related techniques. The first and simplest goal is the assignment of nonparametric

standard errors to a real-valued statistic. More ambitiously, we consider setting nonparametric confidence intervals for a real-valued parameter. Building on the well understood case of confidence intervals for the median, some hopeful evidence is presented that such a theory may be possible.

#### **Efron: Nonparametric standard errors and confidence intervals: Rejoinder**

**Efron-1981b**

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Bradley Efron. “Nonparametric standard errors and confidence intervals: Rejoinder”. In: *The Canadian Journal of Statistics / La Revue Canadienne de Statistique* 9.2 (1981), pp. 170–172. DOI: [10.2307/3314610](https://doi.org/10.2307/3314610).

#### **Efron: Better bootstrap confidence intervals**

**Efron-1987**

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Bradley Efron. “Better bootstrap confidence intervals”. In: *Journal of the American Statistical Association* 82.397 (Mar. 1987), pp. 171–185. DOI: [10.1080/01621459.1987.10478410](https://doi.org/10.1080/01621459.1987.10478410).

Abstract: We consider the problem of setting approximate confidence intervals for a single parameter  $\theta$  in a multiparameter family. The standard approximate intervals based on maximum likelihood theory,  $\hat{\theta} \pm \hat{\sigma}z^{(\alpha)}$ , can be quite misleading. In practice, tricks based on transformations, bias corrections, and so forth, are often used to improve their accuracy. The bootstrap confidence intervals discussed in this article automatically incorporate such tricks without requiring the statistician to think them through for each new application, at the price of a considerable increase in computational effort. The new intervals incorporate an improvement over previously suggested methods, which results in second-order correctness in a wide variety of problems. In addition to parametric families, bootstrap intervals are also developed for nonparametric situations.

#### **Efron: Bootstrap confidence intervals: Good or bad?**

**Efron-1988**

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Bradley Efron. “Bootstrap confidence intervals: Good or bad?” In: *Psychological Bulletin* 104.2 (1988), pp. 293–296. DOI: [10.1037/0033-2909.104.2.293](https://doi.org/10.1037/0033-2909.104.2.293).

Abstract: The bootstrap is a nonparametric technique for estimating standard errors and approximate confidence intervals. Rasmussen has used a simulation experiment to suggest that bootstrap confidence intervals perform very poorly in the estimation of a correlation coefficient. Part of Rasmussen's simulation is repeated. A careful look at the results shows the bootstrap intervals performing quite well. Some remarks are made concerning the virtues and defects of bootstrap intervals in general.

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**Gollob et al.: Taking account of time lags in causal models**      **Gollob-Reichardt-1987**

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Harry F. Gollob and Charles S. Reichardt. "Taking account of time lags in causal models". In: *Child Development* 58.1 (Feb. 1987), p. 80. ISSN: 0009-3920. DOI: [10.2307/1130293](https://doi.org/10.2307/1130293).

Abstract: Although it takes time for a cause to exert an effect, causal models often fail to allow adequately for time lags. In particular, causal models that contain cross-sectional relations (i. e., relations between values of 2 variables at the same time) are unsatisfactory because (a) they omit the values of variables at prior times, (b) they omit effects that variables can have on themselves, and (c) they fail to specify the length of the causal interval that is being studied. These omissions can produce severe biases in estimates of the size of causal effects. Longitudinal models also can fail to take account of time lags properly, and this too can lead to severely biased estimates. The discussion illustrates the biases that can occur in both cross-sectional and longitudinal models, introduces the latent longitudinal approach to causal modeling, and shows how latent longitudinal models can be used to reduce bias by taking account of time lags even when data are available for only 1 point in time.

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**James et al.: Mediators, moderators, and tests for mediation**      **James-Brett-1984**

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Lawrence R. James and Jeanne M. Brett. "Mediators, moderators, and tests for mediation". In: *Journal of Applied Psychology* 69.2 (1984), pp. 307–321. DOI: [10.1037/0021-9010.69.2.307](https://doi.org/10.1037/0021-9010.69.2.307).

Abstract: Discusses mediation relations in causal terms. Influences of an antecedent are transmitted to a consequence through an intervening mediator. Mediation relations may assume a number of functional forms, including nonadditive, nonlinear, and nonrecursive forms. Although mediation and moderation are distinguishable processes, with nonadditive forms (moderated mediation) a particular variable may be both a mediator and a moderator within a single set of functional relations. Current models for testing mediation relations in industrial and organizational psychology often involve an interplay between exploratory (correlational) statistical tests and causal inference. It is suggested that no middle ground exists between exploratory and confirmatory (causal) analysis and that attempts to explain how mediation processes occur require specified causal models.

**Judd et al.: Process analysis**

**Judd-Kenny-1981**

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Charles M. Judd and David A. Kenny. "Process analysis". In: *Evaluation Review* 5.5 (Oct. 1981), pp. 602–619. DOI: [10.1177/0193841x8100500502](https://doi.org/10.1177/0193841x8100500502).

Abstract: This article presents the rationale and procedures for conducting a process analysis in evaluation research. Such an analysis attempts to identify the process that mediates the effects of some treatment, by estimating the parameters of a causal chain between the treatment and some outcome variable. Two different procedures for estimating mediation are discussed. In addition we present procedures for examining whether a treatment exerts its effects, in part, by altering the mediating process that produces the outcome. Finally, the benefits of process analysis in evaluation research are underlined.

**Kaplan et al.: Pathways to adolescent drug use: Self-derogation, peer influence, weakening of social controls, and early substance use**

**Kaplan-Martin-Robbins-1984**

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Howard B. Kaplan, Steven S. Martin, and Cynthia Robbins. "Pathways to adolescent drug use: Self-derogation, peer influence, weakening of social controls, and early substance use". In: *Journal of Health and Social Behavior* 25.3 (Sept. 1984), p. 270. ISSN: 0022-1465. DOI: [10.2307/2136425](https://doi.org/10.2307/2136425).

Abstract: We test a model that accounts for the adoption of drug use among adolescents in terms of four explanatory perspectives: self-derogation, peer influence, social control, and early substance use. The data come from a three-wave panel study of junior high school students in Houston ( $N = 3,052$ ). Using nine variables at Time 1, 10 variables at Time 2, and drug use at Time 3, we operationalize components of all four theoretical perspectives in a path model predicting drug use. Results indicate that the four theoretical perspectives complement each other in predicting subsequent adoption of drug use. Significant primary and intervening roles can be attributed to each of the four perspectives. We discuss these findings in terms of an integrative approach to multivariate models of drug use.

**MacKinnon et al.: Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties** **MacKinnon-White-1985**

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James G. MacKinnon and Halbert White. "Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties". In: *Journal of Econometrics* 29.3 (Sept. 1985), pp. 305–325. DOI: [10.1016/0304-4076\(85\)90158-7](https://doi.org/10.1016/0304-4076(85)90158-7).

Abstract: We examine several modified versions of the heteroskedasticity-consistent covariance matrix estimator of Hinkley (1977) and White (1980). On the basis of sampling experiments which compare the performance of quasi t-statistics, we find that one estimator, based on the jackknife, performs better in small samples than the rest. We also examine the finite-sample properties of using modified critical values based on Edgeworth approximations, as proposed by Rothenberg (1984). In addition, we compare the power of several tests for heteroskedasticity, and find that it may be wise to employ the jackknife heteroskedasticity-consistent covariance matrix even in the absence of detected heteroskedasticity.

**Micceri: The unicorn, the normal curve, and other improbable creatures**

Micceri-1989

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Theodore Micceri. “The unicorn, the normal curve, and other improbable creatures”. In: *Psychological Bulletin* 105.1 (1989), pp. 156–166. DOI: [10.1037/0033-2909.105.1.156](https://doi.org/10.1037/0033-2909.105.1.156).

**Newey et al.: A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix**

Newey-West-1987

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Whitney K. Newey and Kenneth D. West. “A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix”. In: *Econometrica* 55.3 (May 1987), p. 703. DOI: [10.2307/1913610](https://doi.org/10.2307/1913610).

**Rasmussen: Estimating correlation coefficients: Bootstrap and parametric approaches**

Rasmussen-1987

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Jeffrey L. Rasmussen. “Estimating correlation coefficients: Bootstrap and parametric approaches”. In: *Psychological Bulletin* 101.1 (1987), pp. 136–139. DOI: [10.1037/0033-2909.101.1.136](https://doi.org/10.1037/0033-2909.101.1.136).

Abstract: The bootstrap, a computer-intensive approach to statistical data analysis, has been recommended as an alternative to parametric approaches. Advocates claim it is superior because it is not burdened by potentially unwarranted normal theory assumptions and because it retains information about the form of the original sample. Empirical support for its superiority, however, is quite limited. The present article compares the bootstrap and parametric approaches to estimating confidence intervals and Type I error rates of the correlation coefficient. The parametric approach is superior to the bootstrap under both assumption violation and nonviolation. The bootstrap results in overly restricted confidence intervals and overly liberal Type I error rates.



Nathaniel Schenker. “Better bootstrap confidence intervals: Comment”. In: *Journal of the American Statistical Association* 82.397 (Mar. 1987), p. 192. DOI: [10.2307/2289150](https://doi.org/10.2307/2289150).

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**Sobel: Asymptotic confidence intervals for indirect effects in structural equation models**

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**Sobel-1982**

Michael E. Sobel. “Asymptotic confidence intervals for indirect effects in structural equation models”. In: *Sociological Methodology* 13 (1982), p. 290. DOI: [10.2307/270723](https://doi.org/10.2307/270723).

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**Sobel: Some new results on indirect effects and their standard errors in covariance structure models**

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**Sobel-1986**

Michael E. Sobel. “Some new results on indirect effects and their standard errors in covariance structure models”. In: *Sociological Methodology* 16 (1986), p. 159. DOI: [10.2307/270922](https://doi.org/10.2307/270922).

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**Sobel: Direct and indirect effects in linear structural equation models**

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**Sobel-1987**

Michael E. Sobel. “Direct and indirect effects in linear structural equation models”. In: *Sociological Methods & Research* 16.1 (Aug. 1987), pp. 155–176. DOI: [10.1177/0049124187016001006](https://doi.org/10.1177/0049124187016001006).

Abstract: This article discusses total indirect effects in linear structural equation models. First, I define these effects. Second, I show how the delta method may be used to obtain the standard errors of the sample estimates of these effects and test hypotheses about the magnitudes of the indirect effects. To keep matters simple, I focus throughout on a particularly simple linear structural equation system; for a treatment of the general case, see Sobel (1986). To illustrate the ideas and results, a detailed example is presented.

**Venzon et al.: A method for computing profile-likelihood-based confidence intervals**

**Venzon-Moolgavkar-1988**

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D. J. Venzon and S. H. Moolgavkar. “A method for computing profile-likelihood-based confidence intervals”. In: *Applied Statistics* 37.1 (1988), p. 87. DOI: [10.2307/2347496](https://doi.org/10.2307/2347496).

Abstract: The method of constructing confidence regions based on the generalised likelihood ratio statistic is well known for parameter vectors. A similar construction of a confidence interval for a single entry of a vector can be implemented by repeatedly maximising over the other parameters. We present an algorithm for finding these confidence interval endpoints that requires less computation. It employs a modified Newton-Raphson iteration to solve a system of equations that defines the endpoints.

**White: A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity**

**White-1980**

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Halbert White. “A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity”. In: *Econometrica* 48.4 (May 1980), pp. 817–838. DOI: [10.2307/1912934](https://doi.org/10.2307/1912934).

Abstract: This paper presents a parameter covariance matrix estimator which is consistent even when the disturbances of a linear regression model are heteroskedastic. This estimator does not depend on a formal model of the structure of the heteroskedasticity. By comparing the elements of the new estimator to those of the usual covariance estimator, one obtains a direct test for heteroskedasticity, since in the absence of heteroskedasticity, the two estimators will be approximately equal, but will generally diverge otherwise. The test has an appealing least squares interpretation.