LUMIVERO

TESTING MEDIATING AND MODERATING EFFECTS USING THE PROCESS MACRO

Renaud Lunardo, PhD, HDR
Kedge Business School, Bordeaux
Email: renaud.lunardo@kedgebs.com
April, 6th

About me…

LOUISIANA TECH UNIVERSITY

HEC MONTRÉAL

Duke UNIVERSITY

University of South Australia

La Cité du Vin
un monde de cultures

VIN & SOCIÉTÉ
AU NOM DES 500 000 ACTEURS DE LA VIGNE ET DU VIN

Hennessy
LES VISITES

Château Canon
1er Grand Cru Classé
Saint-Emilion

CHÂTEAU RAUZAN-SÉGLA
GRAND CRU CLASSÉ
MARGAUX

How do consumers respond to fun wine labels?

Renaud Lunardo
Department of Marketing, Kedge Business School, Talence, France, and
Bradley Rickard
Cornell University, Ithaca, New York, USA and Kedge Business School, Talence, France

Consumers response to fun wine labels

2603

Food Quality and Preference

The narcissistic wine consumer: How social attractiveness associated with wine prompts narcissists to engage in wine consumption

Renaud Lunardo, David A. Jaud, Armando Maria Corni

LUMIVERO

Agenda

- The concepts of moderation and mediation
- The PROCESS macro (Hayes): definition and advantages
- An application in the field of marketing

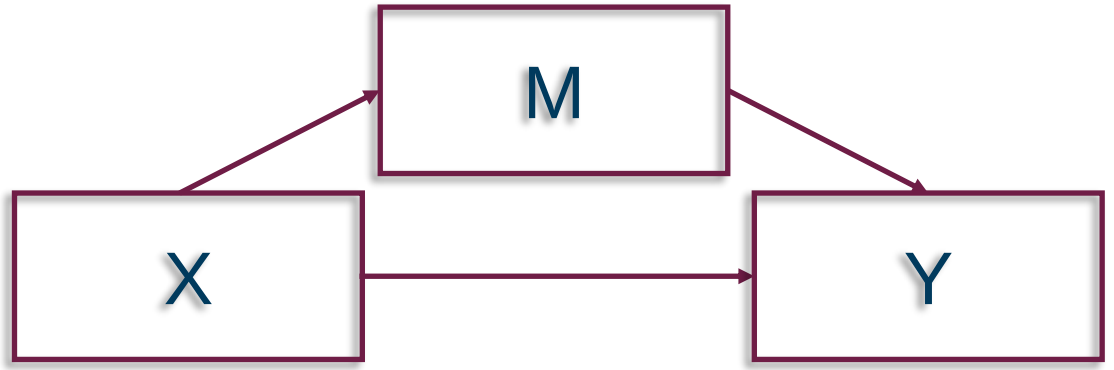
The concepts of moderation and mediation

01

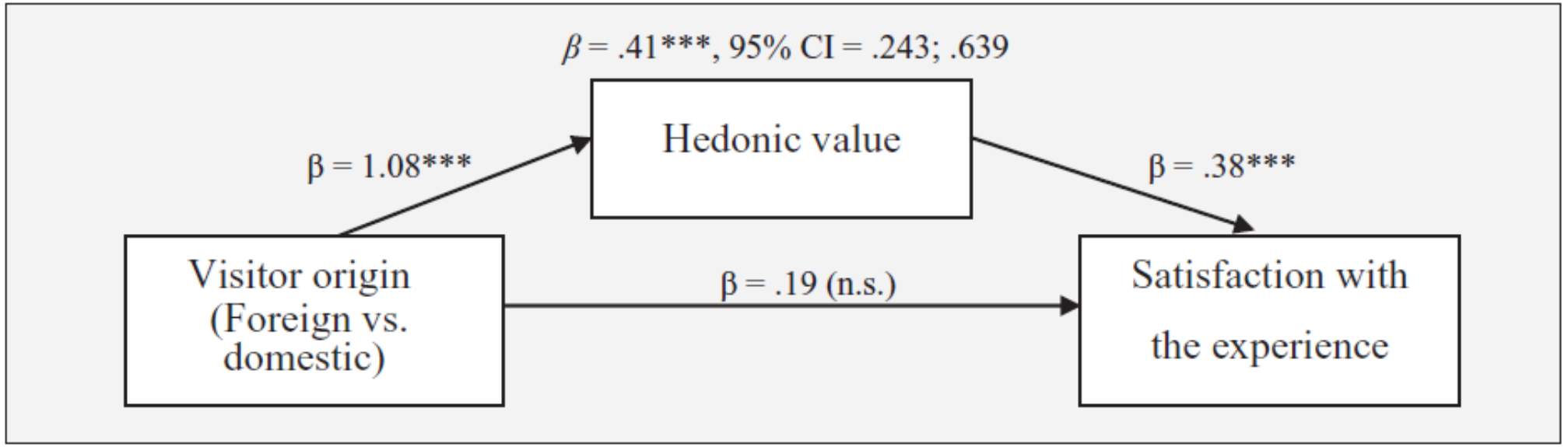
Mediating (i.e., indirect) effects

GOAL:

- Identify the **mechanism** that explains why X has an effect on Y
- Even better: rule out some other potential alternative mechanisms



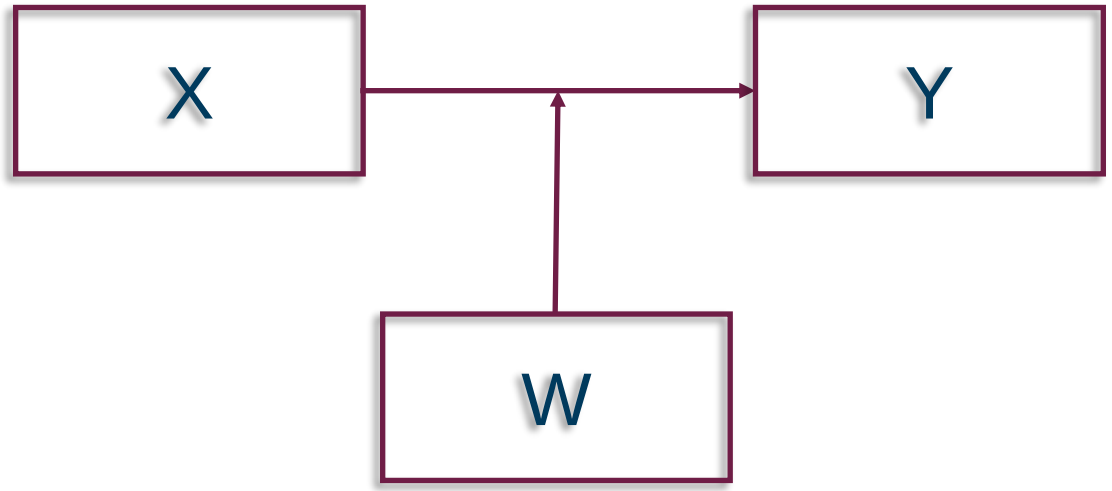
An example of mediating effect



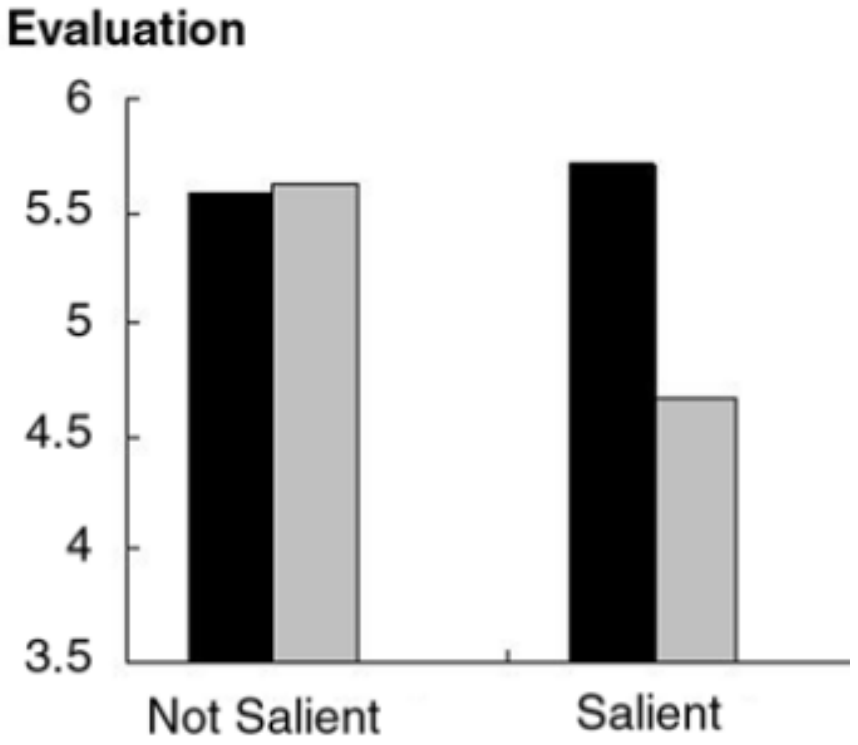
Moderating effects

GOAL: identify the **<u>conditions</u>** under which:

- X has an effect on Y…
- … the effect of X on Y changes (or, the boundary condition for the effect of X on Y)



Reporting moderating effects… depending on X and Z

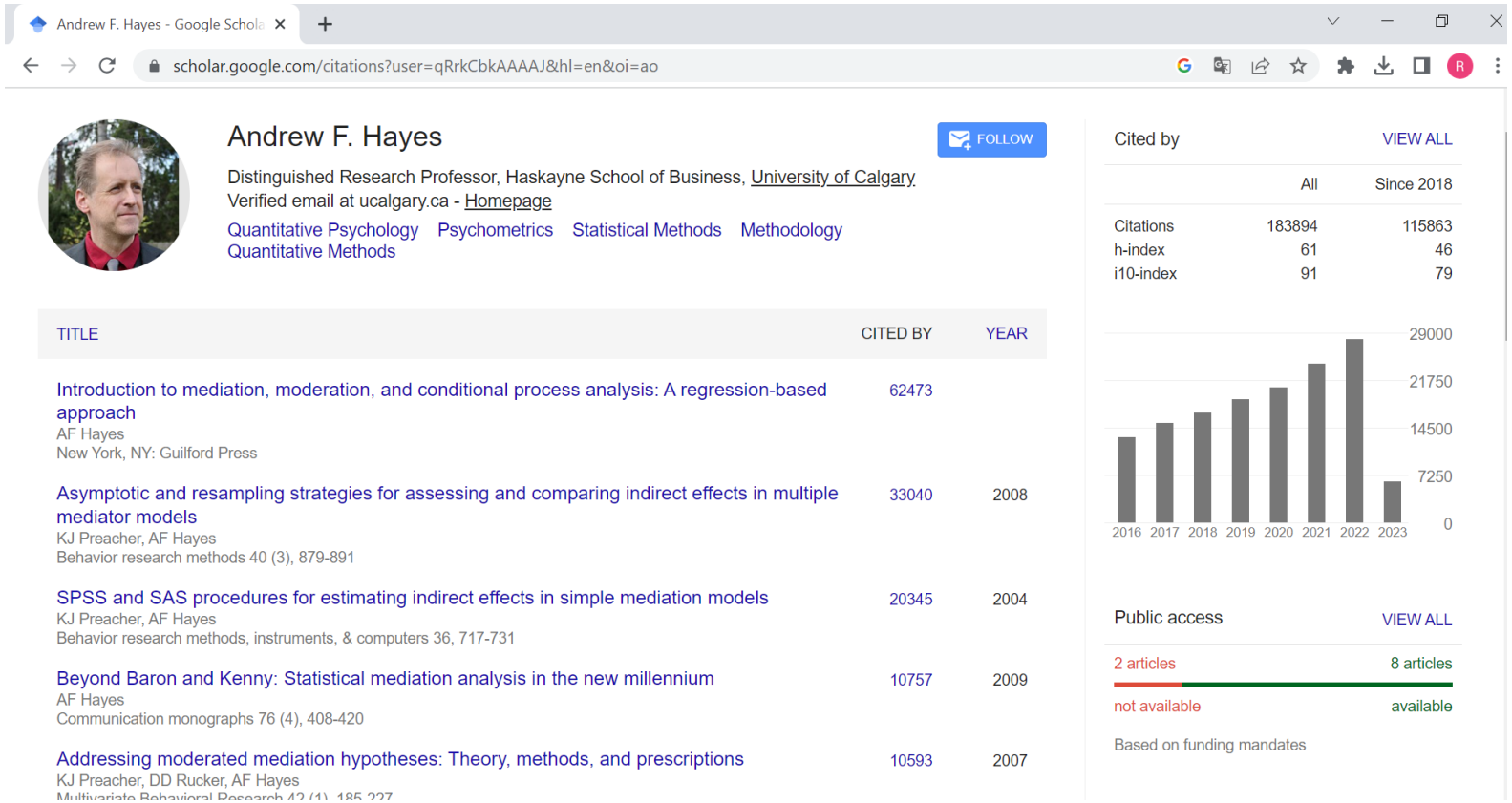


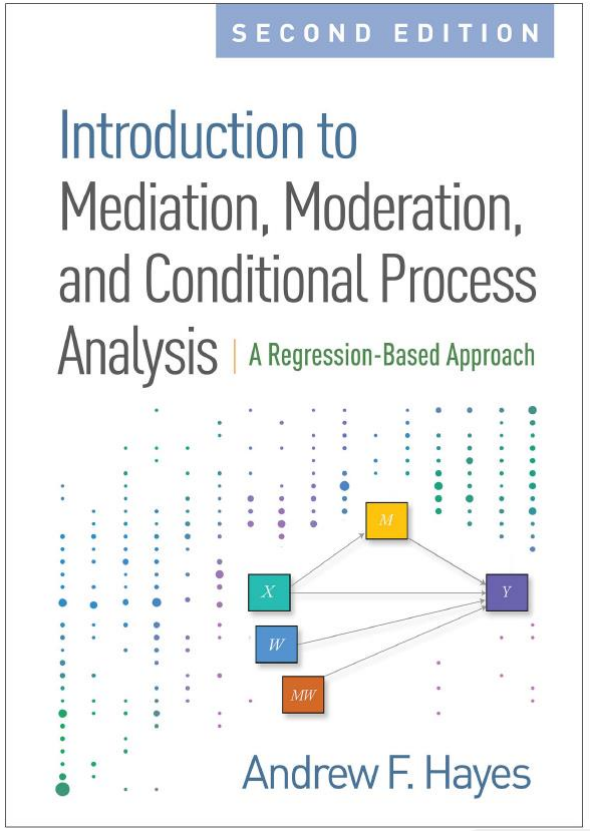
The Macro PROCESS (Hayes)

Definition and advantages

02

At the origin of the Process macro…





MEDIATIONS

Some historical perspective on mediations

Journal of Personality and Social Psychology
1986, Vol. 51, No. 6, 1173-1182

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0022-3514/86/$00.75

The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations

Reuben M. Baron and David A. Kenny
University of Connecticut

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.

The purpose of this analysis is to distinguish between the properties of moderator and mediator variables in such a way as to clarify the different ways in which conceptual variables may account for differences in peoples' behavior. Specifically, we differentiate between two often-confused functions of third variables: (a) the moderator function of third variables, which partitions a focal independent variable into subgroups that establish its domains of maximal effectiveness in regard to a given dependent variable, and (b) the mediator function of a third variable, which represents the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest.

Although these two functions of third variables have a relatively long tradition in the social sciences, it is not at all uncommon for social psychological researchers to use the terms *moderator* and *mediator* interchangeably. For example, Harkins, Latané, and Williams (1980) first summarized the impact of identifiability on social loafing by observing that it "moderates social loafing" (p. 303) and then within the same paragraph proposed "that identifiability is an important mediator of social loafing." Similarly, Findley and Cooper (1983), intending a moderator interpretation, labeled gender, age, race, and socioeconomic level as mediators of the relation between locus of control and academic achievement. Thus, one largely pedagogical function of this article is to clarify for experimental researchers the importance of respecting these distinctions.

This is not, however, the central thrust of our analysis. Rather, our major emphasis is on contrasting the moderator–mediator functions in ways that delineate the implications of this distinction for theory and research. We focus particularly on the differential implications for choice of experimental design, research operations, and plan of statistical analysis.

We also claim that there are conceptual implications of the failure to appreciate the moderator–mediator distinction. Among the issues we will discuss in this regard are missed opportunities to probe more deeply into the nature of causal mechanisms and integrate seemingly irreconcilable theoretical positions. For example, it is possible that in some problem areas disagreements about mediators can be resolved by treating certain variables as moderators.

The moderator and mediator functions will be discussed at three levels: conceptual, strategic, and statistical. To avoid any misunderstanding of the moderator–mediator distinction by erroneously equating it with the difference between experimental manipulations and measured variables, between situational and person variables, or between manipulations and verbal self-reports, we will describe both actual and hypothetical examples involving a wide range of variables and operations. That is, moderators may involve either manipulations or assessments and either situational or person variables. Moreover, mediators are in no way restricted to verbal reports or, for that matter, to individual-level variables.

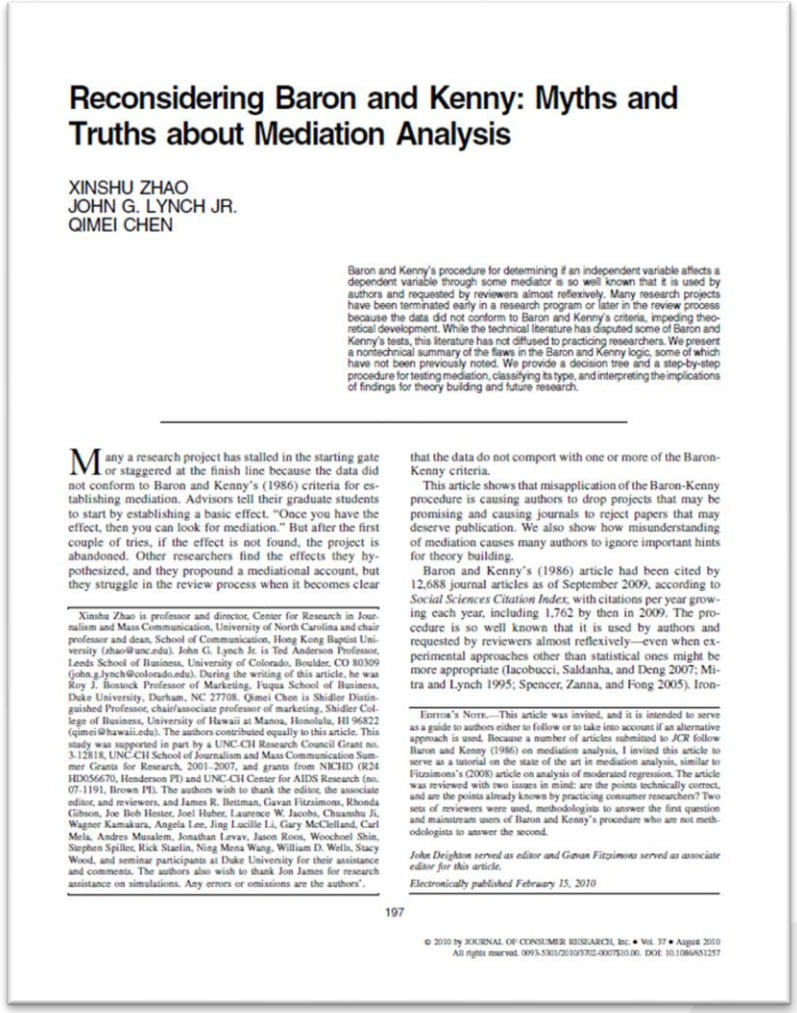
Finally, for expository reasons, our analysis will initially stress the need to make clear whether one is testing a moderator or a mediator type of model. In the second half of the article, we provide a design that allows one to test within the structure of the same study whether a mediator or moderator interpretation is more appropriate.

Although these issues are obviously important for a large number of areas within psychology, we have targeted this article for a social psychological audience because the relevance of this distinction is highest in social psychology, which uses experi-

This research was supported in part by National Science Foundation Grant BNS-8210137 and National Institute of Mental Health Grant R01MH-40295-01 to the second author. Support was also given to him during his sabbatical year (1982–83) by the MacArthur Foundation at the Center for Advanced Studies in the Behavioral Sciences, Stanford, California.

Thanks are due to Judith Harackiewicz, Charles Judd, Stephen West, and Harris Cooper, who provided comments on an earlier version of this article. Stephen P. Needel was instrumental in the beginning stages of this work.

Correspondence concerning this article should be addressed to Reuben M. Baron, Department of Psychology U-20, University of Connecticut, Storrs, Connecticut 06268.



Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis

XINSHU ZHAO
JOHN G. LYNCH JR.
QIMEI CHEN

Baron and Kenny's procedure for determining if an independent variable affects a dependent variable through some mediator is so well known that it is used by authors and requested by reviewers almost reflexively. Many research projects have been terminated early in a research program or later in the review process because the data did not conform to Baron and Kenny's criteria, impeding theoretical development. While the technical literature has disputed some of Baron and Kenny's tests, this literature has not diffused to practicing researchers. We present a nontechnical summary of the flaws in the Baron and Kenny logic, some of which have not been previously noted. We provide a decision tree and a step-by-step procedure for testing mediation, classifying its type, and interpreting the implications of findings for theory building and future research.

Many a research project has stalled in the starting gate or staggered at the finish line because the data did not conform to Baron and Kenny's (1986) criteria for establishing mediation. Advisors tell their graduate students to start by establishing a basic effect. "Once you have the effect, then you can look for mediation." But after the first couple of tries, if the effect is not found, the project is abandoned. Other researchers find the effects they hypothesized, and they propound a mediational account, but they struggle in the review process when it becomes clear that the data do not comport with one or more of the Baron-Kenny criteria.

This article shows that misapplication of the Baron-Kenny procedure is causing authors to drop projects that may be promising and causing journals to reject papers that may deserve publication. We also show how misunderstanding of mediation causes many authors to ignore important hints for theory building.

Baron and Kenny's (1986) article had been cited by 12,688 journal articles as of September 2009, according to *Social Sciences Citation Index*, with citations per year growing each year, including 1,762 by then in 2009. The procedure is so well known that it is used by authors and requested by reviewers almost reflexively—even when experimental approaches other than statistical ones might be more appropriate (Iacobucci, Saldanha, and Deng 2007; Mitra and Lynch 1995; Spencer, Zanna, and Fong 2005). Iron-

Xinshu Zhao is professor and director, Center for Research in Journalism and Mass Communication, University of North Carolina and chair professor and dean, School of Communication, Hong Kong Baptist University (zhao@unc.edu). John G. Lynch Jr. is Ted Anderson Professor, Leeds School of Business, University of Colorado, Boulder, CO 80309 (john.g.lynch@colorado.edu). During the writing of this article, he was Roy J. Bostock Professor of Marketing, Fuqua School of Business, Duke University, Durham, NC 27708. Qimei Chen is Shidler Distinguished Professor, chair/associate professor of marketing, Shidler College of Business, University of Hawaii at Manoa, Honolulu, HI 96822 (qimei@hawaii.edu). The authors contributed equally to this article. This study was supported in part by a UNC-CH Research Council Grant no. 3-12818, UNC-CH School of Journalism and Mass Communication Summer Grants for Research, 2001–2007, and grants from NICHD (R24 HD056670, Henderson PI) and UNC-CH Center for AIDS Research (no. 07-1191, Brown PI). The authors wish to thank the editor, the associate editor, and reviewers, and James R. Bettman, Gavan Fitzsimons, Rhonda Gibson, Joe Bob Hester, Joel Huber, Laurence W. Jacobs, Chuanshu Ji, Wagner Kamakura, Angela Lee, Jing Lucille Li, Gary McClelland, Carl Mela, Andres Musalem, Jonathan Levav, Jason Roos, Woocheol Shin, Stephen Spiller, Rick Staelin, Ning Mena Wang, William D. Wells, Stacy Wood, and seminar participants at Duke University for their assistance and comments. The authors also wish to thank Jon James for research assistance on simulations. Any errors or omissions are the authors'.

EDITOR'S NOTE.—This article was invited, and it is intended to serve as a guide to authors either to follow or to take into account if an alternative approach is used. Because a number of articles submitted to *JCR* follow Baron and Kenny (1986) on mediation analysis, I invited this article to serve as a tutorial on the state of the art in mediation analysis, similar to Fitzsimons's (2008) article on analysis of moderated regression. The article was reviewed with two issues in mind: are the points technically correct, and are the points already known by practicing consumer researchers? Two sets of reviewers were used, methodologists to answer the first question and mainstream users of Baron and Kenny's procedure who are not methodologists to answer the second.

John Deighton served as editor and Gavan Fitzsimons served as associate editor for this article.

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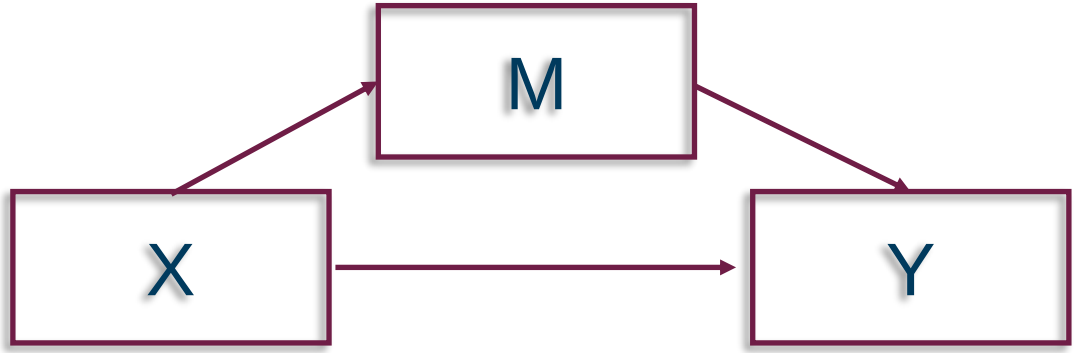
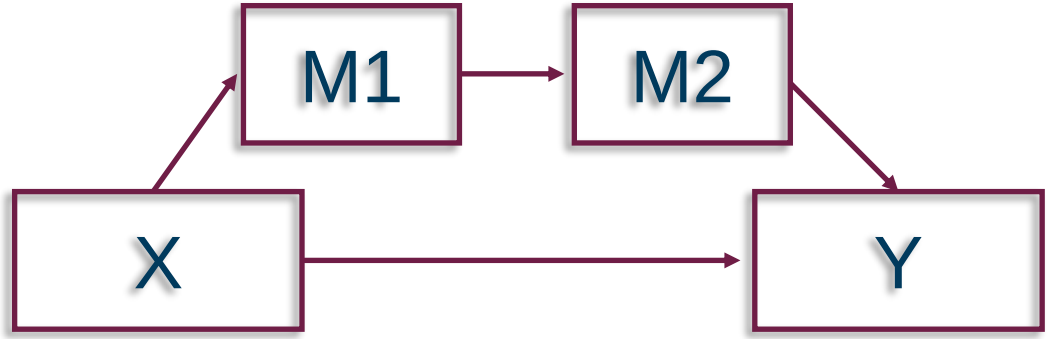
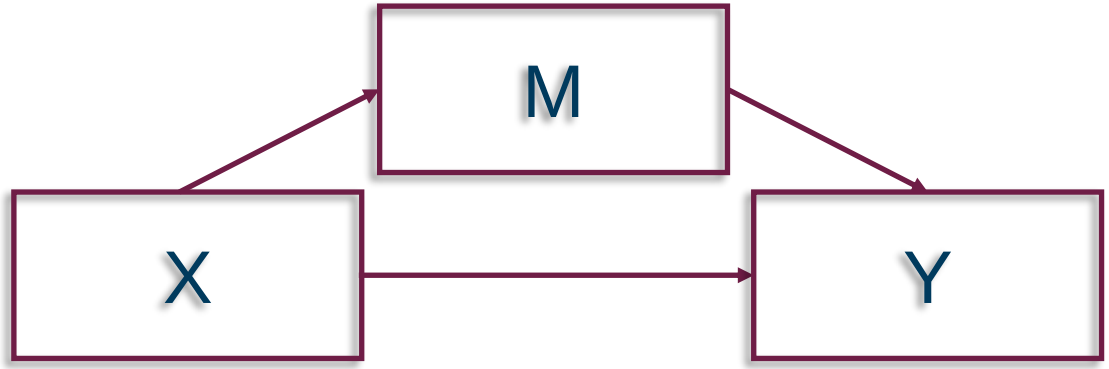
Mediation effects





The 4-step old (1986…) fashion way of testing mediation



$$Y = i_1 + cX + e_1, \quad 1.$$

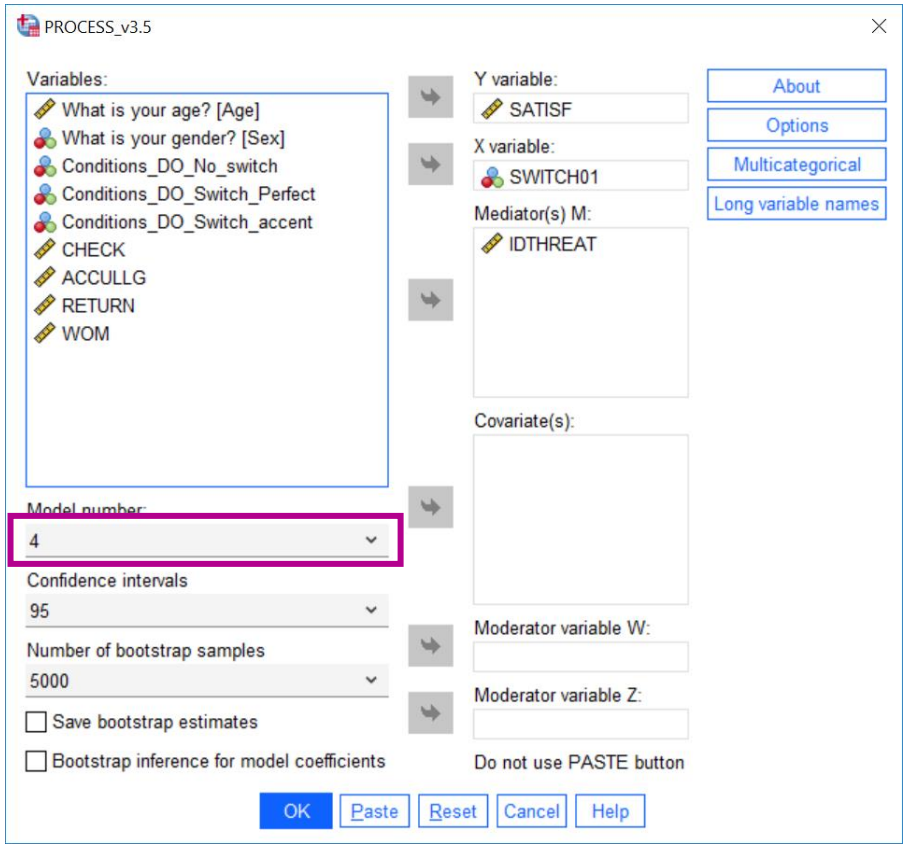
$$Y = i_2 + c'X + bM + e_2, \quad 2.$$

$$M = i_3 + aX + e_3, \quad 3.$$

1. Significant relation of X to the Y in eq. 1
2. Significant relation of X to M in eq. 3
3. M significantly related to Y when both X and M are predictors of Y in eq. 2
4. Non-significant coefficient relating X to Y in eq. 2

Baron, R. M. , & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology,* 51, 1173–1182.

Testing mediation using the Process macro



Model : 4 Y : SATISF X : SWITCH01 M : IDTHREAT

****

OUTCOME VARIABLE: IDTHREAT

	coeff	se	t	p	LLCI	ULCI
constant	2,3143	,1918	12,0678	,0000	1,9361	2,6925
SWITCH01	1,3485	,2331	5,7842	,0000	,8888	1,8083

****

OUTCOME VARIABLE: SATISF

	coeff	se	t	p	LLCI	ULCI
constant	6,1991	,1656	37,4358	,0000	5,8725	6,5256
SWITCH01	-,0267	,1653	-,1616	,8718	-,3528	,2993
IDTHREAT	-,3120	,0465	-6,7087	,0000	-,4038	-,2203

****** DIRECT AND INDIRECT EFFECTS OF X ON Y *********

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-,0267	,1653	-,1616	,8718	-,3528	,2993

Indirect effect(s) of X on Y:

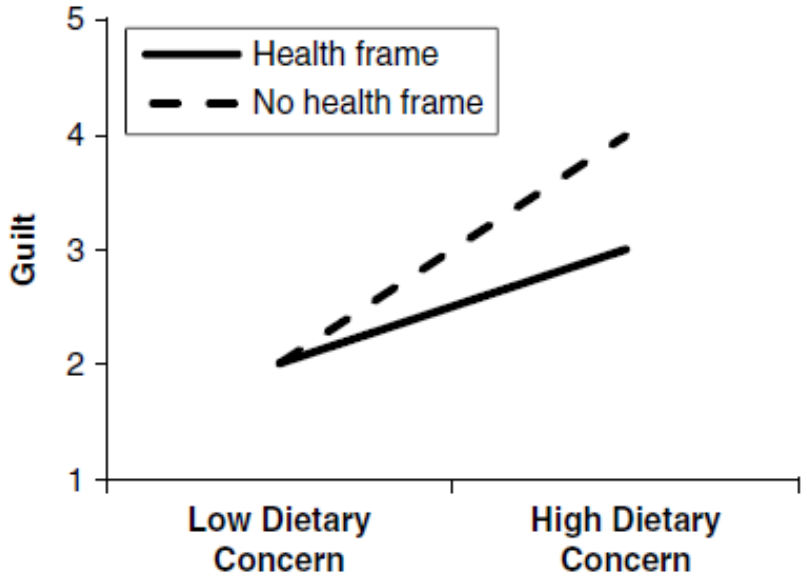
	Effect	BootSE	BootLLCI	BootULCI
IDTHREAT	-,4208	,0997	-,6315	-,2418

Testing moderations: what NOT to do…

Performing a split (median- or mean-based) when Z is numerical/continuous

→ Huge controversy around this method due to, among others, **arbitrary value of the split** and **insensitive analysis to the pattern of local covariation between X and Y within groups defined by the median split**

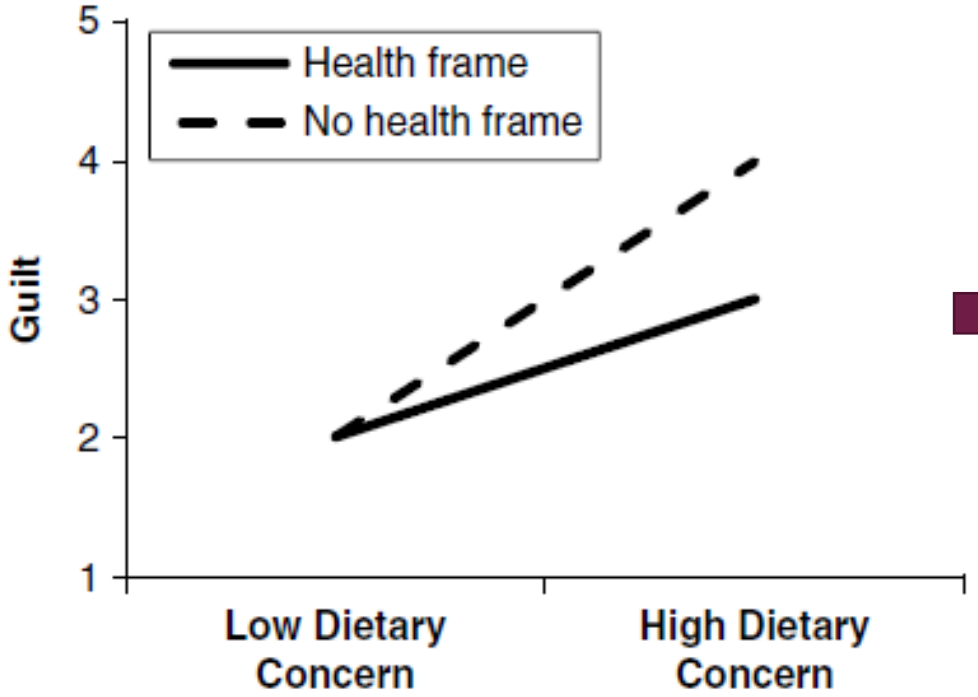
→ « *We know of no statistical argument in favor of median splits to counterbalance the chorus of statistical critiques against them*» (Mc Lelland et al., 2015, p.680).

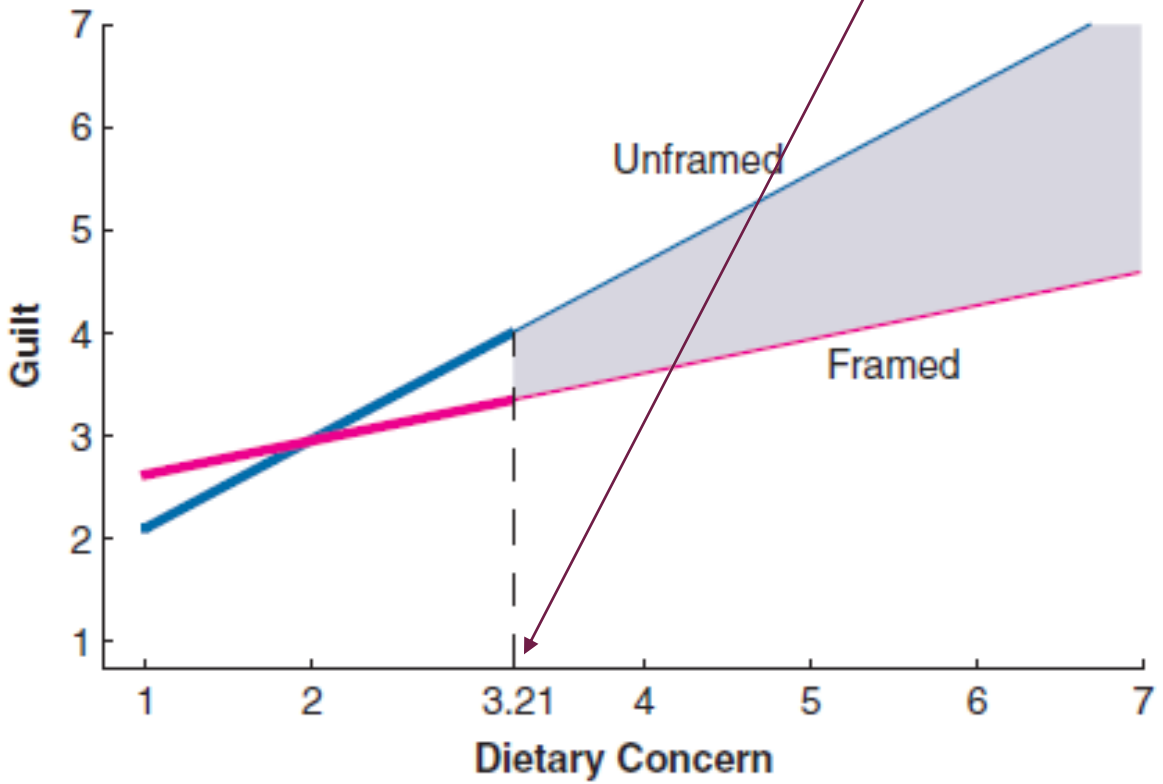


Fitzsimons, G. J. (2008), Death to dichotomizing, *Journal of Consumer Research* 35(1), 5–8.
McClelland, G.H., Lynch, Jr., J.G., Irwin, J.R., Spiller, S.A., & Fitzsimons, G. J. (2015), Median splits, Type II errors, and false–positive consumer psychology: Don't fight the power, *Journal of Consumer Psychology* 25 (4), 679–689.

What TO DO

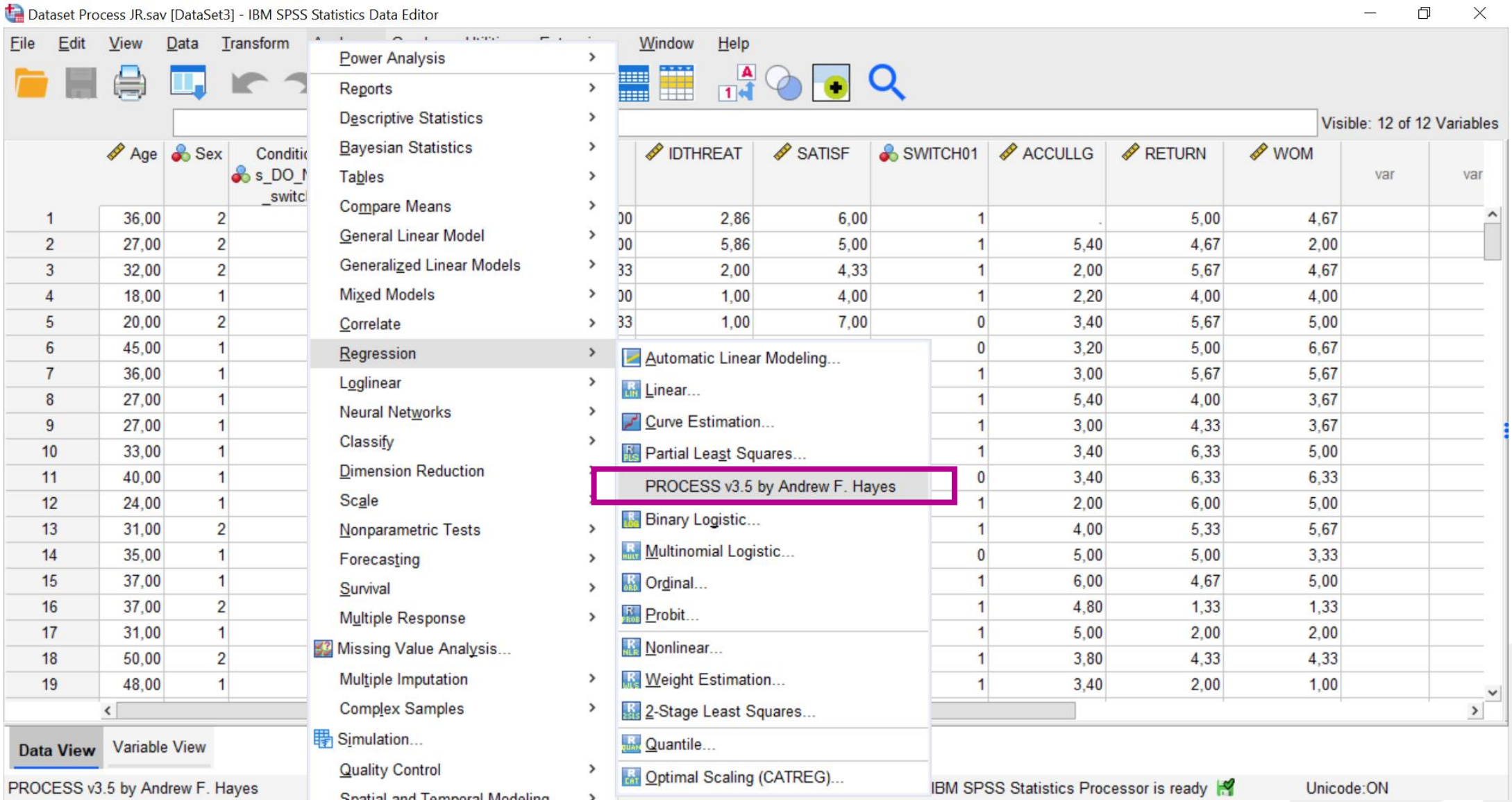
- Keep the continuous measure (i.e., do NOT split)
- Identify the Johnson-Neyman point



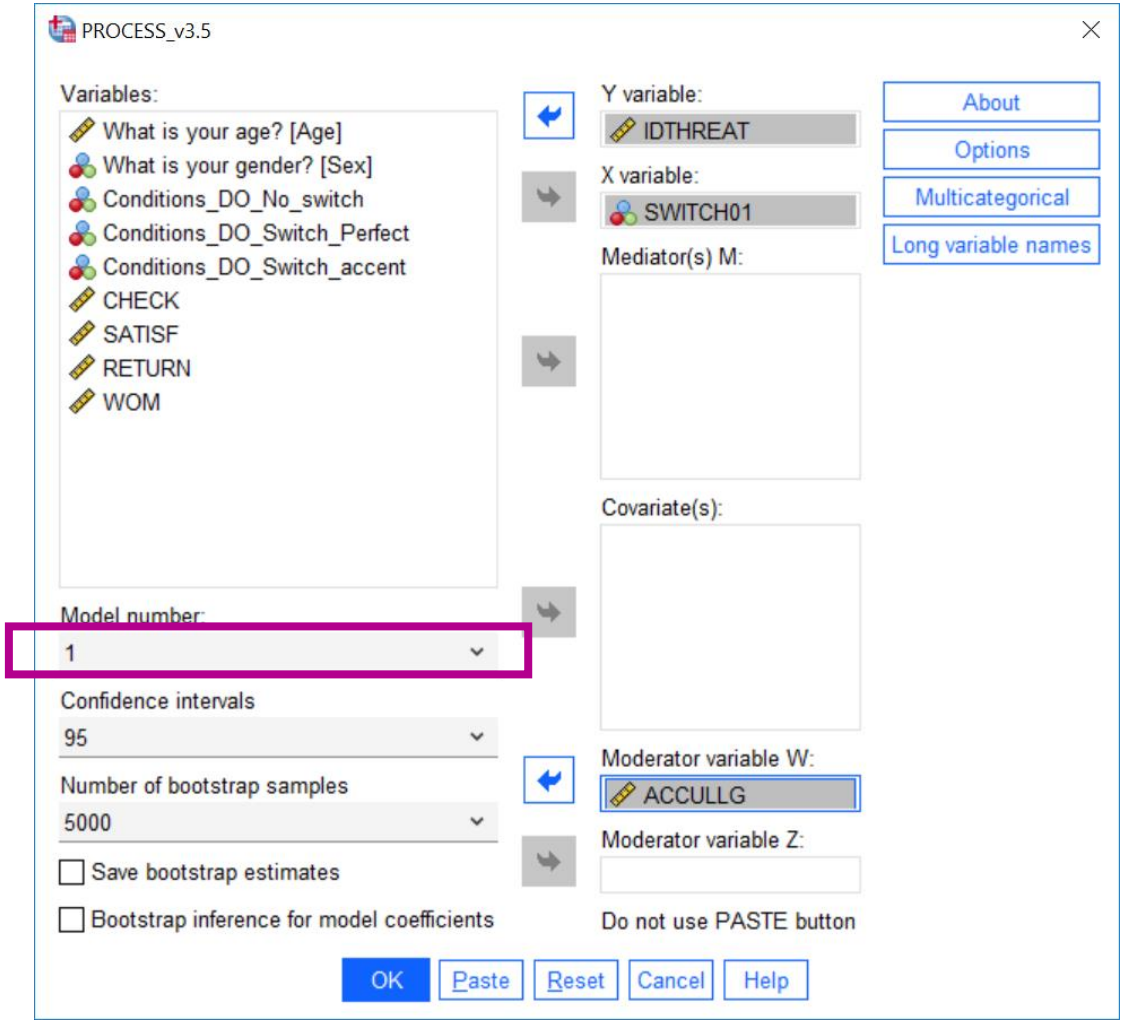


Spiller, S. A., Fitzsimons, G. J., Lynch, Jr. J. G., & McClelland, G.H (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of Marketing Research*, 50, 277-88.

Testing moderation using the Process macro



How to use it




```
OUTCOME VARIABLE:
 IDTHREAT

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5222       ,2727     2,0616    24,4921     3,0000   196,0000       ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,0054       ,6619     3,0298       ,0028      ,7001     3,3108
SWITCH01    -1,1995       ,8325    -1,4409       ,1512    -2,8414      ,4423
ACCULLG       ,0801       ,1654      ,4844       ,6286     -,2460      ,4062
Int_1         ,5963       ,2018     2,9549       ,0035      ,1983      ,9942
```

Tells you if the effect of X on Y depends on Z (or if the simple slopes representing the effect of X on Y significantly differ at different values of Z)

Identifying the Johnson-Neyman point

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
2,9924	10,5000	89,5000

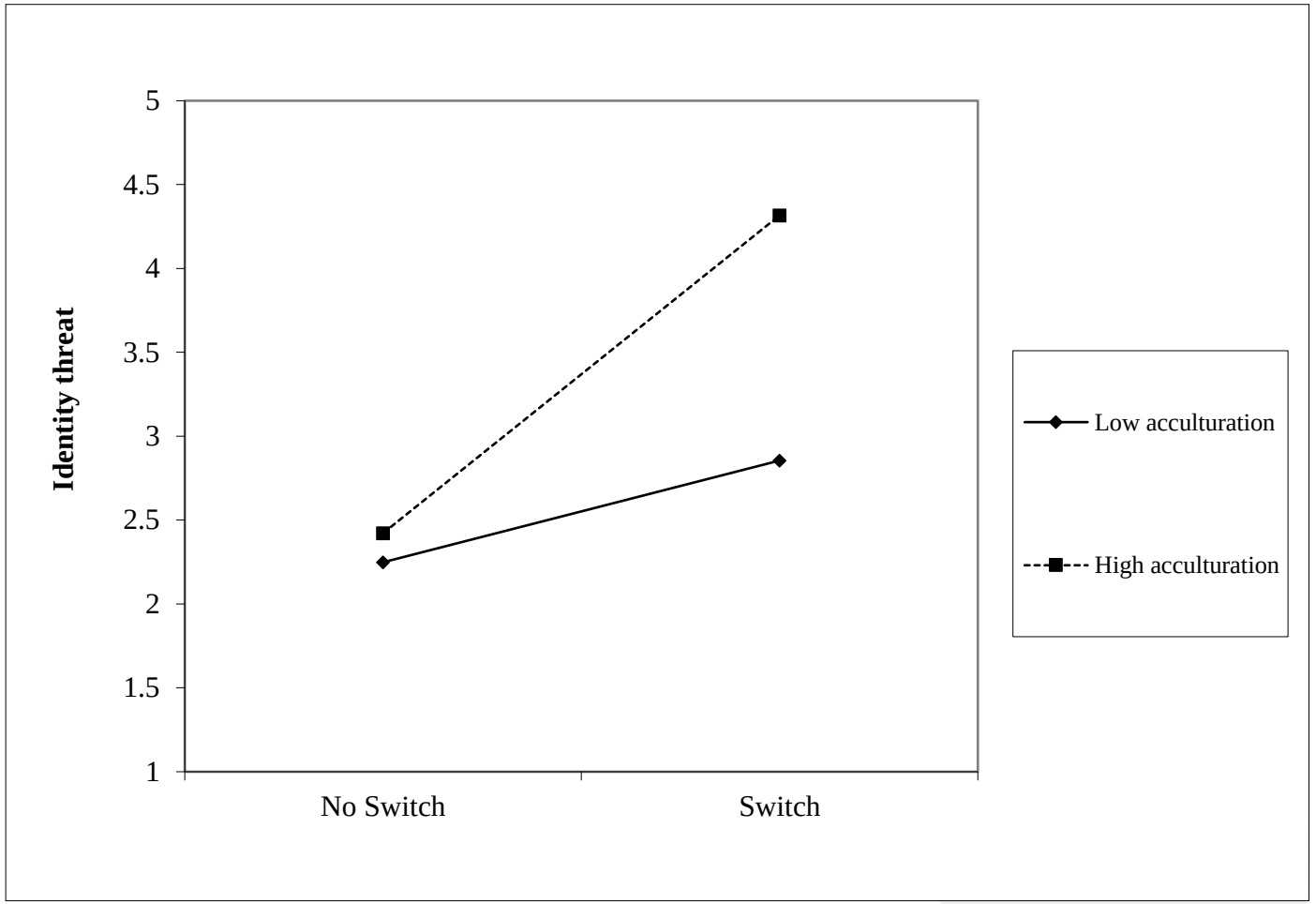
Conditional effect of focal predictor at values of the moderator:

ACCULLG	Effect	se	t	p	LLCI	ULCI
1,2000	-,4840	,6023	-,8035	,4226	-1,6719	,7039
1,4900	-,3111	,5483	-,5674	,5711	-1,3923	,7702
1,7800	-,1382	,4952	-,2790	,7806	-1,1148	,8385
2,0700	,0348	,4435	,0784	,9376	-,8399	,9095
2,3600	,2077	,3938	,5275	,5985	-,5688	,9842
2,6500	,3806	,3467	1,0977	,2737	-,3032	1,0644
2,9400	,5535	,3037	1,8225	,0699	-,0455	1,1525
2,9924	,5848	,2965	1,9721	,0500	,0000	1,1696
3,2300	,7265	,2667	2,7239	,0070	,2005	1,2524
3,5200	,8994	,2384	3,7718	,0002	,4291	1,3696
3,8100	1,0723	,2223	4,8229	,0000	,6338	1,5108
4,1000	1,2452	,2210	5,6334	,0000	,8093	1,6811
4,3900	1,4181	,2348	6,0396	,0000	,9551	1,8812
4,6800	1,5911	,2613	6,0899	,0000	1,0758	2,1063
4,9700	1,7640	,2970	5,9386	,0000	1,1782	2,3498
5,2600	1,9369	,3392	5,7103	,0000	1,2680	2,6058
5,5500	2,1098	,3856	5,4708	,0000	1,3493	2,8704
5,8400	2,2827	,4350	5,2474	,0000	1,4248	3,1407
6,1300	2,4557	,4864	5,0483	,0000	1,4964	3,4150
6,4200	2,6286	,5393	4,8742	,0000	1,5650	3,6921
6,7100	2,8015	,5932	4,7226	,0000	1,6316	3,9714

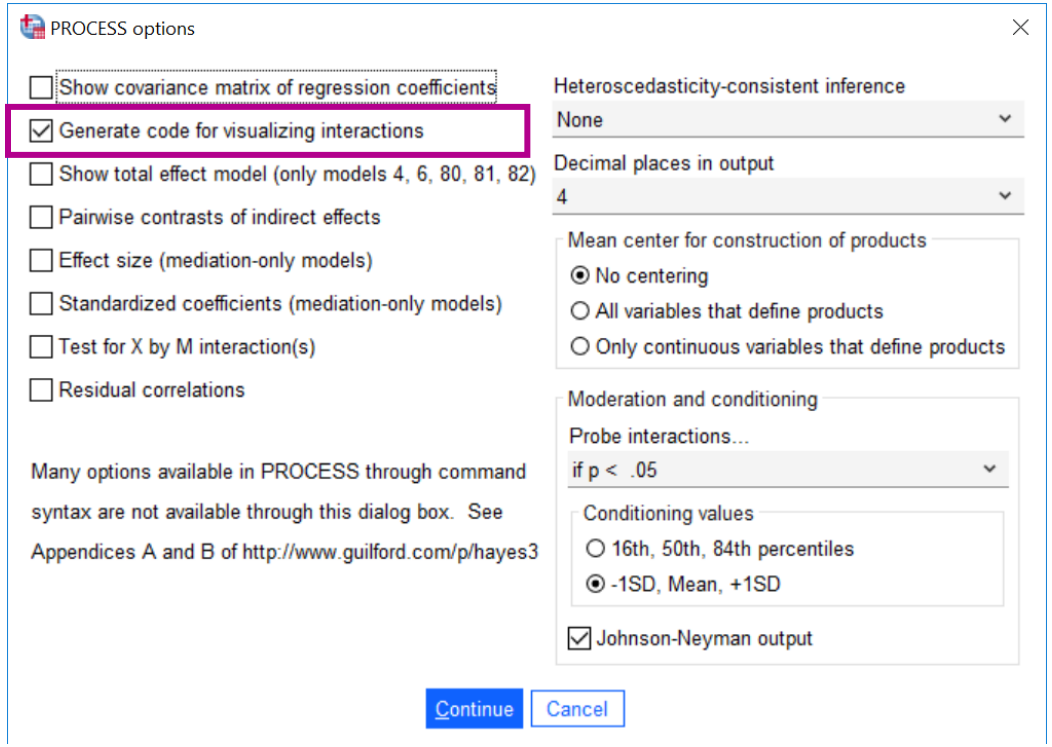
You see that below a value of acculturation of 2.94, the effect of the swicth is non significant (or, in other words, not different from 0, being 95% sure). Hence, the conclusion is that the switch has a positive (check the coef. > 0) effect on identity threat only for values of acculturation greater than 2.99.

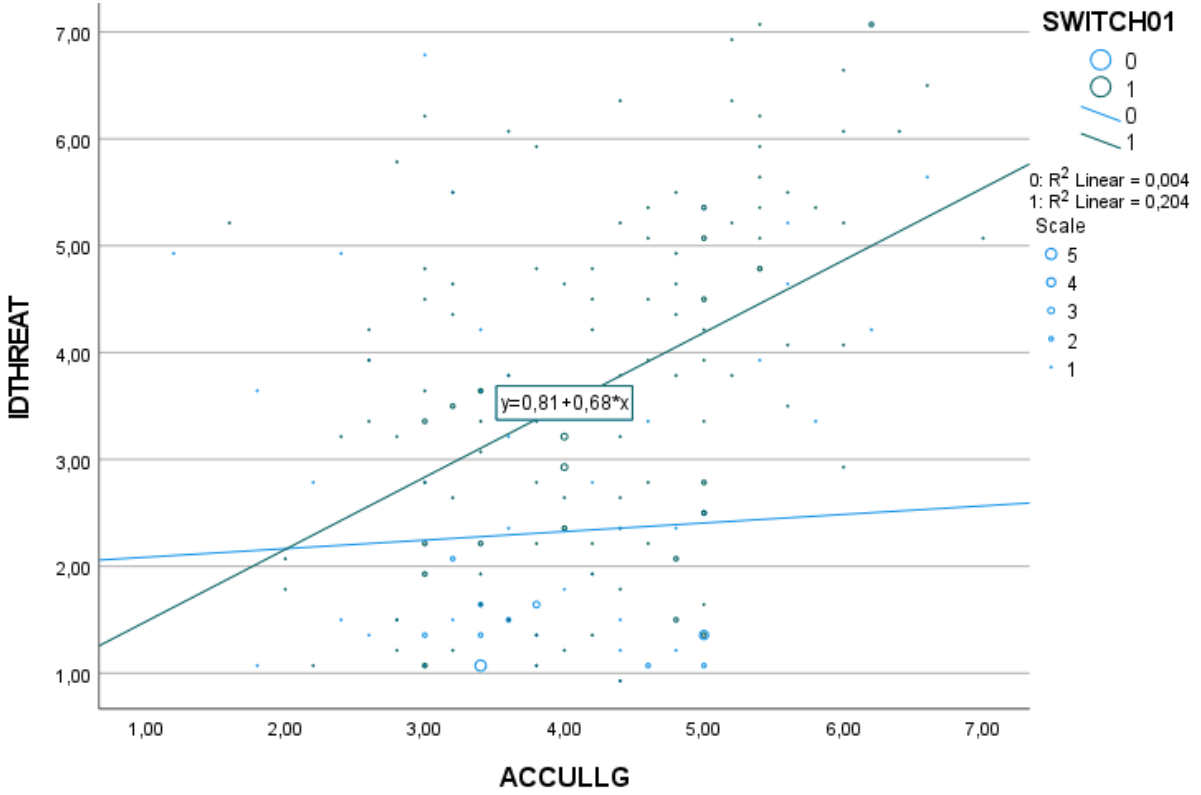
Probing the interaction (http://www.jeremydawson.co.uk/slopes.htm)

Variable names:	
Name of independent variable:	Switch
Name of moderator:	Acculturation
Name of dependent variable:	Identity threat
Unstandardised Regression Coefficients:	
Independent variable:	-1,1995
Moderator:	0,0801
Interaction:	0,5963
Intercept / Constant:	2,0054
Means / SDs of variables:	
Mean of independent variable:	0,68
SD of independent variable:	0,469
Mean of moderator:	4,11
SD of moderator:	1,08
Values of variables at which to plot slopes*:	
Low value of IV:	0
High value of IV:	1
Low value of moderator:	3,03
High value of moderator:	5,19
(If left blank, this will automatically be done at one standard deviation above and below mean)*	
Optional alternative legend:**	
Low value of independent variable:	No Switch
High value of independent variable:	Switch
Low value of moderator:	Low acculturation
High value of moderator:	High acculturation
*(** Leave these cells blank to get the normal "low/high" legend)*	

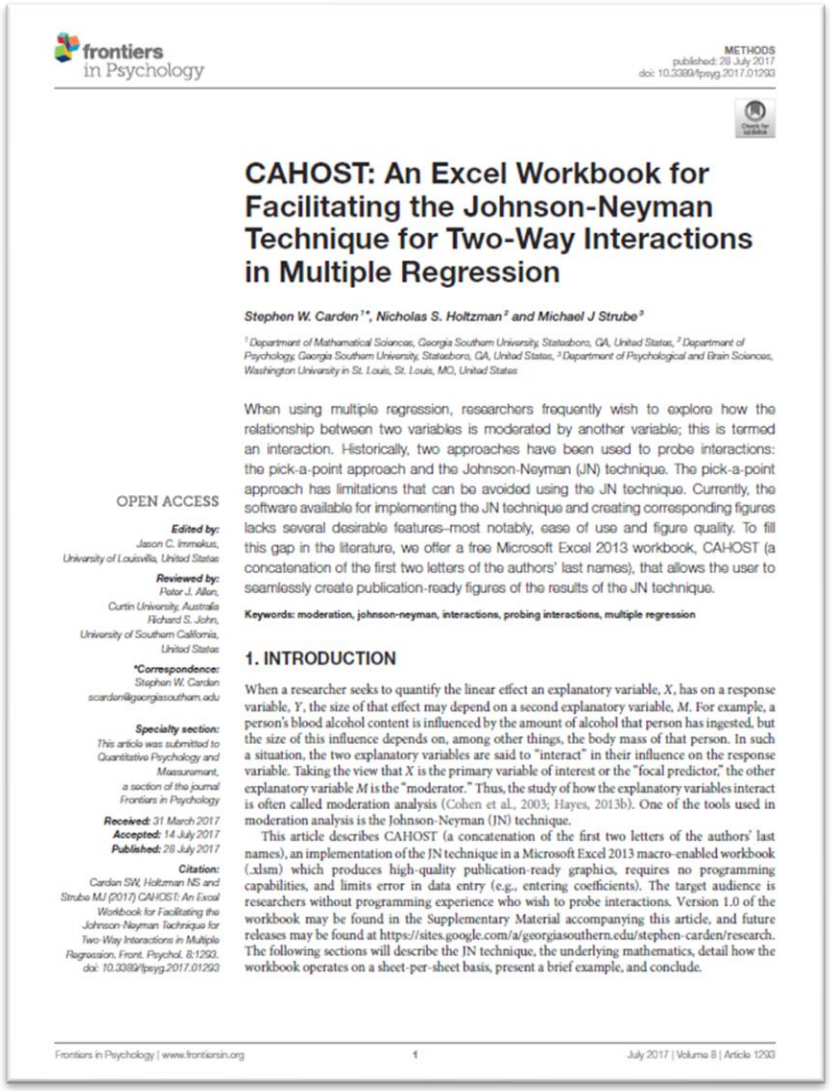


Probing the interaction using SPSS syntax





Probing the interaction using the CAHOST procedure



frontiers in Psychology

METHODS
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CAHOST: An Excel Workbook for Facilitating the Johnson-Neyman Technique for Two-Way Interactions in Multiple Regression

Stephen W. Carden[1]*, Nicholas S. Holtzman[2] and Michael J Strube[3]

[1] Department of Mathematical Sciences, Georgia Southern University, Statesboro, GA, United States, [2] Department of Psychology, Georgia Southern University, Statesboro, GA, United States, [3] Department of Psychological and Brain Sciences, Washington University in St. Louis, St. Louis, MO, United States

When using multiple regression, researchers frequently wish to explore how the relationship between two variables is moderated by another variable; this is termed an interaction. Historically, two approaches have been used to probe interactions: the pick-a-point approach and the Johnson-Neyman (JN) technique. The pick-a-point approach has limitations that can be avoided using the JN technique. Currently, the software available for implementing the JN technique and creating corresponding figures lacks several desirable features–most notably, ease of use and figure quality. To fill this gap in the literature, we offer a free Microsoft Excel 2013 workbook, CAHOST (a concatenation of the first two letters of the authors' last names), that allows the user to seamlessly create publication-ready figures of the results of the JN technique.

Keywords: moderation, johnson-neyman, interactions, probing interactions, multiple regression

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***Correspondence:**
Stephen W. Carden
scarden@georgiasouthern.edu

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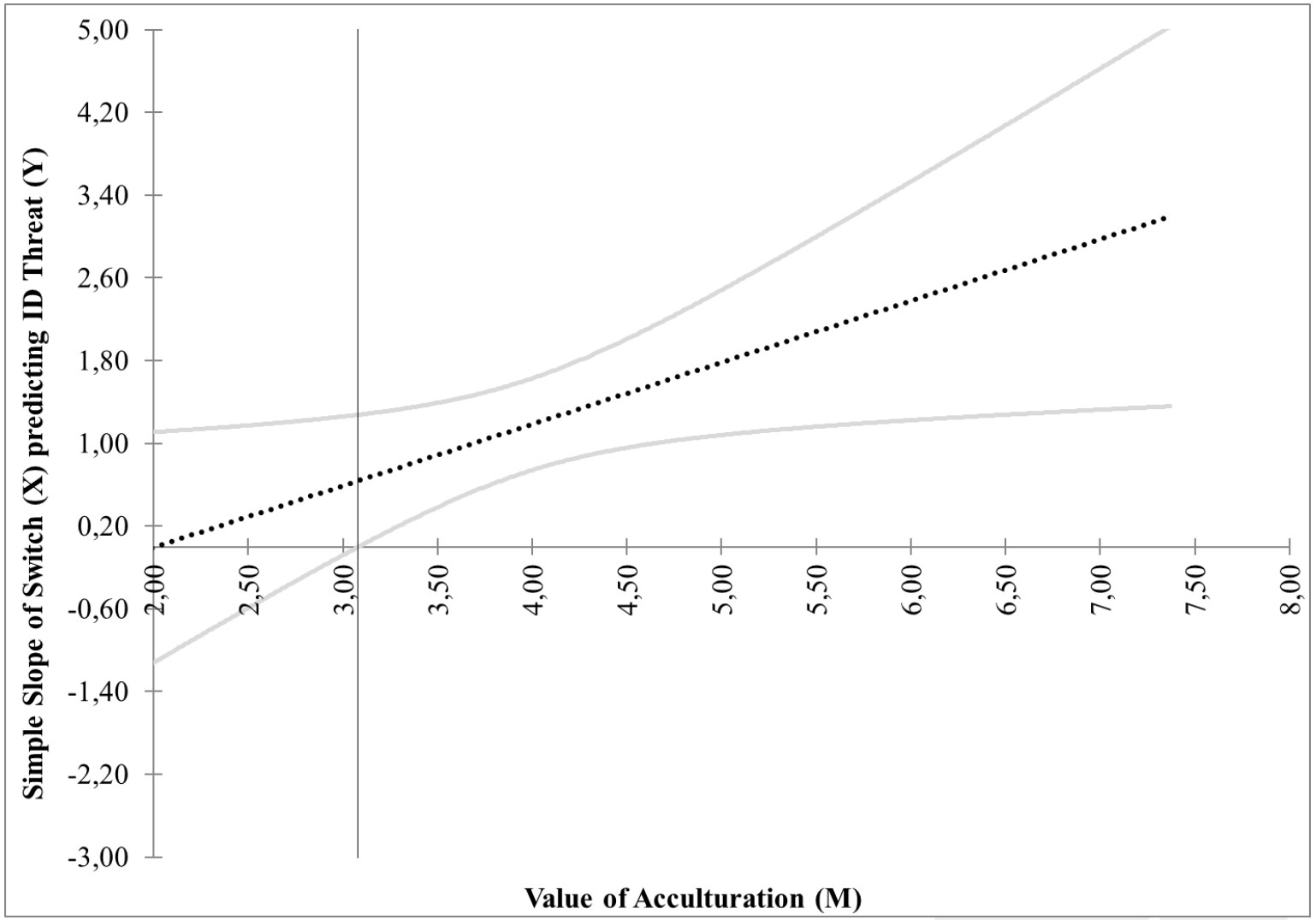
1. INTRODUCTION

When a researcher seeks to quantify the linear effect an explanatory variable, X, has on a response variable, Y, the size of that effect may depend on a second explanatory variable, M. For example, a person's blood alcohol content is influenced by the amount of alcohol that person has ingested, but the size of this influence depends on, among other things, the body mass of that person. In such a situation, the two explanatory variables are said to "interact" in their influence on the response variable. Taking the view that X is the primary variable of interest or the "focal predictor," the other explanatory variable M is the "moderator." Thus, the study of how the explanatory variables interact is often called moderation analysis (Cohen et al., 2003; Hayes, 2013b). One of the tools used in moderation analysis is the Johnson-Neyman (JN) technique.

This article describes CAHOST (a concatenation of the first two letters of the authors' last names), an implementation of the JN technique in a Microsoft Excel 2013 macro-enabled workbook (.xlsm) which produces high-quality publication-ready graphics, requires no programming capabilities, and limits error in data entry (e.g., entering coefficients). The target audience is researchers without programming experience who wish to probe interactions. Version 1.0 of the workbook may be found in the Supplementary Material accompanying this article, and future releases may be found at https://sites.google.com/a/georgiasouthern.edu/stephen-carden/research. The following sections will describe the JN technique, the underlying mathematics, detail how the workbook operates on a sheet-per-sheet basis, present a brief example, and conclude.



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