Antonakis, J. 2016. Testing mediation: The endogeneity problem and the solution. Master Tutorial: Society for Industrial and Organizational Psychology, Anaheim, U.S.A.

MASTER TUTORIAL

TITLE
Testing mediation: The endogeneity problem and the solution

SHORTENED TITLE
Endogeneity in mediation

ABSTRACT
Endogeneity in mediation threatens the validity of research findings. It occurs when the mediator is not exogenous (i.e., not manipulated), which is usual in most I-O research settings. In such instances, using typical methods (e.g., Baron-Kenny, Preacher-Hayes) yields incorrect parameter estimates. I will show how instrumental-variable estimation recovers correct parameters.

PRESS PARAGRAPH
A mediator is a dependent variable, *m* (e.g., charisma), that supposedly channels the effect of an independent variable, *x* (e.g., receiving training or not), on another dependent variable (e.g., subordinate satisfaction), *y*. In experimental settings *x* is manipulated—subjects are randomized to treatment—to isolate the causal effect of *x* on other variables. If *m* is not or cannot be manipulated, which is usually the case, its causal effect on other variables cannot be determined; thus, standard mediation tests cannot inform policy or practice. I will show how an econometric procedure, called instrumental-variable estimation, can examine mediation in such cases.

WORD COUNT
2,957

Mediation is commonly used in I-O psychology; however, it is commonly *mis*-used in I-O psychology (Antonakis, Bendahan, Jacquart, & Lalive, 2010, 2014; Shaver, 2005). Kline (2015) went on to describe a "mediation myth," stating "relatively little of the extant literature on mediation is actually worthwhile" (p. 210).

In this session, I will show (a) what testing mediation really implies and (b) demonstrate why the most commonly-used tests of mediation are actually quite problematic, and (c) introduce a solution to the problem. As mentioned by Smith (2012) in a recently editorial in a top psychology journal, *Journal of Personality and Social Psychology*: "if the independent variable (X) is manipulated and the mediator (M) and dependent variable (Y) are measured, the usual analysis will be biased if unobserved causes of M are correlated with unobserved causes of Y" (p. 2).

What does Smith mean exactly? To provide a background, mediation is used to examine the effect of an independent variable, *x*, on a dependent variable, *y*, via a mediator *m*. The causal chain that is hypothesized is $x \rightarrow m \rightarrow y$. More formally:

$$m = \gamma_0 + \gamma_1 x + v \qquad \text{Eq. 1}$$

$$y = \beta_0 + \beta_1 m + w \qquad \text{Eq. 2}$$

Where *v* and *w* are assumed to be random disturbances (errors), which are orthogonal to *x* and *m*; this orthogonality assumption is critical and if it holds it means that any unmeasured causes of *m* and *y* do not correlate with *x* and *m*. If the above assumptions are met, then the mediation effect, that is, a test of $\gamma_1.\beta_1 = 0$ can be correctly estimated (note, I expressed this test as a null hypothesis test; however, if the researcher has an idea of what the value of the mediation effect should be, it is easy to use a Wald test to examine whether $\gamma_1.\beta_1$ is different from that particular value). If the orthogonality assumptions fail to hold then the mediation effect will not be correctly estimated; violation of this orthogonality assumption is referred to as *endogeneity*.

In this Master Tutorial I will show how mediation analysis should be undertaken to ensure correct causal estimation. I will assume that participants have some basic training in regression and structural equation modeling (SEM) and will focus on the delivery of the following learning objectives:

1. Identifying likely sources of endogeneity in applied psychology research and practice
2. Detailing how endogeneity biases parameter estimates and why the “usual” estimators do not work
3. Showing how instrumental-variable estimation provides a straightforward solution to the problem of endogeneity in mediation.
4. Demonstrating an empirical example of instrumental-variable estimation

I provide more details about what I will say in each section. I will use appropriate slides and examples to bring the below to life.

Learning Objective #1: Identifying sources of endogeneity (10 mins)

In this section I will discuss how endogeneity can occur. I will use vivid and intuitive explanations beginning with a specific example: Suppose that a researcher is interested to see whether charisma can be trained in managers, and whether increases in charisma can affect subordinate satisfaction with the managers. Thus, the mediator, m (e.g., charisma), is thought to channel the effect of a random independent variable, x (e.g., receiving training or not), on another dependent variable (e.g., subordinate satisfaction), y. At this point it should be clear that most theories of mediation present the m as an outcome of x; thus, m by definition is a dependent—or endogenous—variable.

The researcher randomizes managers to a treatment and a control condition (for simplicity assume one "control" condition). By randomizing the managers to conditions, the researcher ensures that, overall, the two groups are interchangeable. That is, assuming a sufficiently large sample size, at the beginning of the experiment the two groups will be roughly equivalent in any observable or unobservable characteristics (Shadish, Cook, & Campbell, 2002). There will be a roughly an equal amount of males and females in both groups, intelligence will be equally distributed across groups, as will be good looks or what have you; we collectively call these characteristics *q*. With randomization we ensure that there is no correlation between *x* and *q* (Antonakis, et al., 2010). If for instance there were smarter managers in the treatment group and being in treatment group was significantly related to *y* it is unclear as to whether treatment group or intelligence is what was responsible for higher scores on *y*; thus, policy decisions resulting from this design could be misguided because the treatment is confounded with initial differences between the groups. With randomization, therefore, we can make a causal claim about *x'*s impact on *m* or on any other variable directly, including *y*, because *x* is exogenous[1].

Endogeneity happens when a regressor is not exogenous. Recall, exogenous means that the variable is random and cannot correlate with anything else except for the variable that it is supposed to cause (assuming of course, that the manipulation happened before the effect). An endogenous variable does not have this property. To help participants understand this issue, I will provide a tangible example of possible endogeneity bias: Assume that having the "right" facial appearance (cf. Antonakis & Dalgas, 2009; Todorov, Mandisodza, Goren, & Hall, 2005; Trichas

[1] The best exogenous variables are those that have been manipulated. However, *x* need not be manipulated; for example, it can be a variable that varies naturally in nature (e.g., temperature), is cyclical (e.g., elections), fixed (e.g., latitude), genetically determined and stable by adulthood (e.g., personality) and so forth (Antonakis, et al., 2014); in such cases, *x* cannot be affected by other variables under study or omitted causes of these variables.

& Schyns, 2012), or being smarter (cf. Judge, Colbert, & Ilies, 2004; Lord, De Vader, & Alliger, 1986) predicts charisma (*m*) and leader outcomes (*y*); *m* is thus endogenous with respect to *y* and both variables share a common causes (i.e., appearance and intelligence) that I will denote as q. Now, if the researcher finds that *m* predicts *y* is that because (a) only of the effect of *x* on *m* to *y* or (b) is it because *m* and *y* both covary with q, which is unmeasured—and thus cannot be controlled for—in the regression model? The estimate of *m* on *y* will be biased if they both depend on an omitted cause, q. The above is just one example of endogeneity in mediation that can threaten the validity of research findings. I will explain in my presentation that there are other sources of endogeneity including measurement error in *m*, *y* affecting *m*, or both *m* and *y* simultaneously affecting each other.

Learning Objective #2: Detailing how endogeneity biases parameter estimates and why the "usual" estimators do not work (20 mins)

Here, I will show analytically (using some basic algebra and covariance algebra how bias is introduced into estimates. It is essential that we "go through the math" so that participants can understand in theory what the problem is when having endogeneity and using the "typical" methods to test mediation.

Using the notation and logic for omitted variables as detailed in Antonakis et al. (2010), and following the above example of an experiment in which the research wishes to examine mediation, suppose that the true model is as follows:

$$m = \lambda_0 + \lambda_1 x + \lambda_2 q + \varepsilon \qquad \text{Eq. 3}$$

$$y = \eta_0 + \eta_1 m + \eta_2 q + \theta \qquad \text{Eq. 4}$$

Where ε and θ are random disturbances, and *x* and q random variables. Suppose that the researcher does not know about q, and estimates instead, the following:

$$m = \omega_0 + \omega_1 x + u \qquad \text{Eq. 5}$$

$$y = \xi_0 + \xi_1 m + o \qquad \text{Eq. 6}$$

The coefficient of Eq. 5, ω_1 will remain unaffected and will equal λ_1 in Eq. 3 asymptotically (i.e., the estimate is said to be consistent in that with an increasing sample size it will converge to the true population value); even though *q* is not included in Eq. 5, and its effects are thus pooled in *u*, the coefficient ω_1 is still consistent because *x* is exogenous and will not correlate with omitted causes of *m*. Thus, there is no problem in Eq. 5. Let us focus on Eq. 6, where there is a problem, because both *m* and *y* correlate with *q* and the effect of *q* is pooled in *o*. To see how, we first model the relation between *q* and *m* (they correlate). The direction of the causal relation is not relevant here; we can thus write out *q* as a function of *m* (and omit the constant for simplicity):

$$q = \kappa_1 m + \varphi \qquad \text{Eq. 7}$$

Substituting Eq. 7 into Eq. 4 shows:

$$y = \eta_0 + \eta_1 m + \eta_2(\kappa_1 m + \varphi) + \theta \qquad \text{Eq. 8}$$

Multiplying out gives:

$$y = \eta_0 + \eta_1 m + (\underbrace{\eta_2 \kappa_1 m + \eta_2 \varphi + \theta}_{o}) \qquad \text{Eq. 9}$$

Notice, that *o* in Eq. 6 is a “super-disturbance” actually consisting of $\eta_2 \kappa_1 m + \eta_2 \varphi + \theta$ as indicated in Eq. 9. Rearranging as function of *m* gives:

$$y = \eta_0 + (\eta_1 + \eta_2 \kappa_1) m + \eta_2 \varphi + \theta \qquad \text{Eq. 10}$$

Thus, the OLS (ordinary least squares) or ML (maximum likelihood) estimate of $\xi_1$in Eq. 6 will be biased because

$$\xi_1 = \frac{cov(y,m)}{var(m)} = \eta_1 + \eta_2 \kappa_1 \neq \eta_1 \qquad \text{Eq. 11}$$

ξ_1 will only equal η_1 if either η_2 or κ_1 are zero. Or seen differently the coefficient of η_1 in Eq. 4 is (Pedhazur, 1997),

$$\eta_1 = \frac{Var(q)*Cov(y,m) - Cov(q,m)*Cov(y,q)}{Var(q)*Var(m) - Cov(q,m)^2} \neq \frac{cov(y,m)}{var(m)} \quad \text{Eq. 12}$$

Thus, in the presence of endogeneity, typical estimation procedures used in I-O psychology such as (a) the regression procedures of Baron and Kenny (1986), Preacher and Hayes (2004), or (b) structural equation model (Edwards & Lambert, 2007) will not work because they assume that *m* is exogenous; that is, the procedures usually estimate Eq. 6, when testing full mediation (or they estimate a partial mediation model, see Eq. 13 below, which also assumes *m* to be exogenous). No amount of bootstrapping—as per the Preacher and Hayes guidelines—of an inconsistent coefficient will render it consistent. Additionally, testing a "partial mediation" in the presence of endogeneity will also produce inconsistent estimates. That is, suppose the researcher estimates:

$$y = \mu_0 + \mu_1 m + \mu_2 x + i \quad \text{Eq. 13}$$

Both μ_1 and μ_2 will now be inconsistent because the endogeneity bias that affects the coefficient of *m* will also affect the coefficient of *x* given that these two variables are correlated and the bias is transmitted via that correlation (Antonakis, et al., 2010). Thus, μ_1 (in Eq. 13) $\neq \eta_1$ (in Eq. 4).

The endogeneity problem and relevant assumptions made in testing mediation *have been acknowledged* by Edwards and Lambert (2007, p. 19) and Baron and Kenny (1986, p. 1177). However, the assumptions are almost wholly ignored by most applied researchers, as is the solution (Antonakis, et al., 2010). I discuss the solution to the problem next.

Learning Objective #3: Showing how instrumental-variable estimation provides a straightforward solution to the problem of endogeneity in mediation (20 mins).

In this section, I will show a simple solution to the problem of endogeneity in mediation. Again, I first show the "math" so that participants understand the intuition behind the estimation procedure. I will also explain the solution graphically, using Venn diagrams.

Following from above, we know that *x* is an exogenous variable that predicts the endogenous variable *m*, as captured by coefficient λ_1 from Eq. 3.

The reduced form model for the direct effect of *x* on *y* can be written as:

$$y = \beta_0 + \Pi x + w \qquad \text{Eq. 14}$$

Where $\Pi = \eta_1 * \lambda_1$. Thus, if we harness the exogeneity of *x* (called the "instrument"), the predicted value of the coefficient of η_1 is (see Angrist & Pischke, 2008):

$$\hat{\eta}_1 = \frac{\widehat{\Pi}}{\hat{\lambda}_1} = \frac{Cov(y,x)/Var(x)}{Cov(m,x)/Varx} = \frac{Cov(y,x)}{Cov(m,x)} \qquad \text{Eq. 15}$$

The above is the general formula for an instrumental-variable estimate (e.g., see Bollen, 2012).What is clear from the above is that *x*, the instrument, must correlate with *y* and *m* if *m* is a true cause of *y;* else, the estimate of Eq. 15 is either zero or undefined, which shows up another fallacy in mediation—and a widely believed one too—that *x* need not correlate with *y* to establish mediation (Shrout & Bolger, 2002; Zhao, Lynch, & Chen, 2010).

Note, from Eq. 15 we know that (and substituting Eq. 4 into the numerator of Eq. 15):

$$\hat{\eta}_1 = \frac{Cov(y,x)}{Cov(m,x)} = \frac{Cov(\eta_0+\eta_1 m+\eta_2 q+\theta,x)}{Cov(m,x)} \qquad \text{Eq. 16}$$

Expanding and dropping constants, as well as the disturbance, which is orthogonal to *x* too gives:

$$\hat{\eta}_1 = \frac{Cov(\eta_1 m,x)+Cov(\eta_2 q,x)}{Cov(m,x)} \qquad \text{Eq. 17}$$

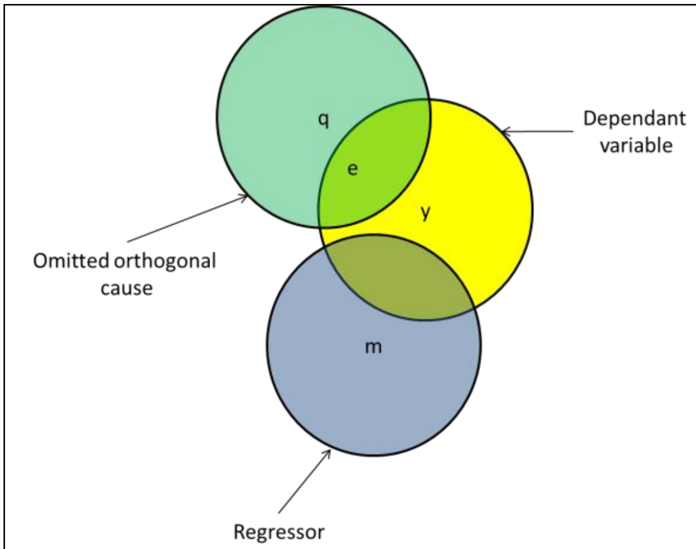
$$\hat{\eta}_1 = \frac{\eta_1 Cov(m,x)+\eta_2 Cov(q,x)}{Cov(m,x)} \qquad \text{Eq. 18}$$

$$\hat{\eta}_1 = \eta_1 + \frac{\eta_2 Cov(q,x)}{Cov(m,x)} \quad \text{Eq. 19}$$

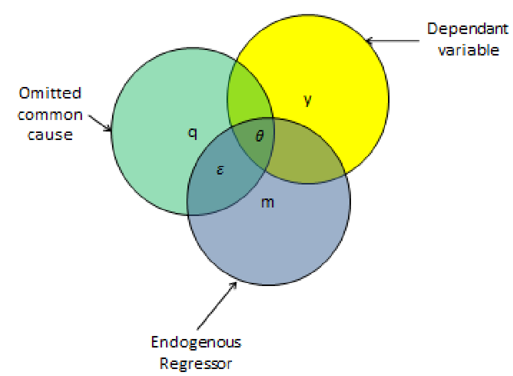
If the instrument is exogenous, that is, does not correlate with the omitted cause (q), then it is obvious that the instrumental variable estimate from Eq. 15, $\hat{\eta}_1 = \eta_1$ (from Eq. 4).

Instrumental variable estimation can be achieved with two-stage least squares (a least squares, closed-form estimator), which uses the predicted value of *m* from Eq. 5 (stemming from *x*), $\widehat{m}$, as the regressor in Eq. 6; it can also be accomplished via ML estimation, whereby the disturbances of Eq. 5 and Eq. 6, that is *u* and *o* are correlated (Antonakis, et al., 2010).

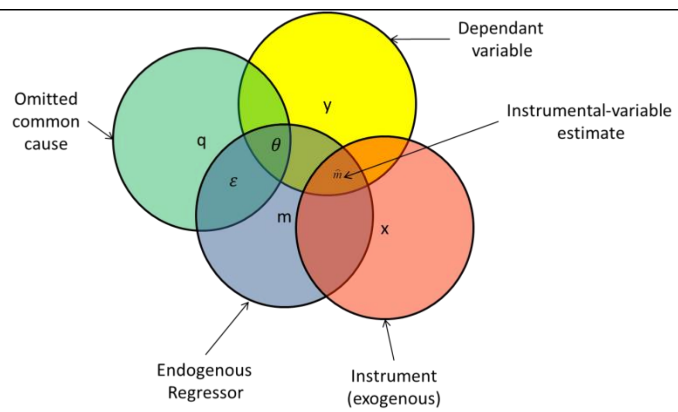
The problem and the solution can also be expressed in Venn diagrams, where the overlap in circles depicts shared variance in the variables (see Kennedy, 2008)—for simplification, I only show one omitted case of y, *q*:



Case 1: the regressor m is exogenous (q does not overlap with m); thus the estimate of y regressed on m will be consistent.



Case 2: the regressor, m is endogenous because q overlaps with m and y. The estimate of y regressed on m will be inconsistent because of the green-yellow-blue overlap.



Case 3: x is exogenous, and thus does not correlate with omitted causes of y (or m). Using an instrumental variable estimator, that is, the proportion of overlap of x with y and x with m will give an estimate using $\widehat{m}$, which is isolated from both ε and θ.

Learning Objective #4: Demonstrate an empirical example of instrumental-variable estimation and the "wrong way" (20 mins.)

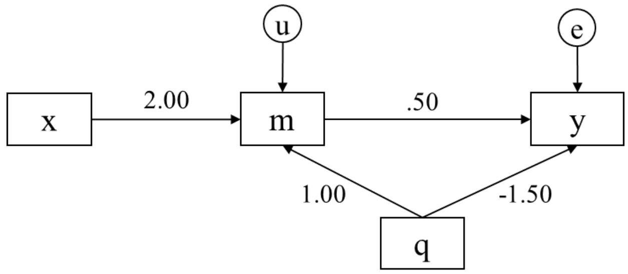
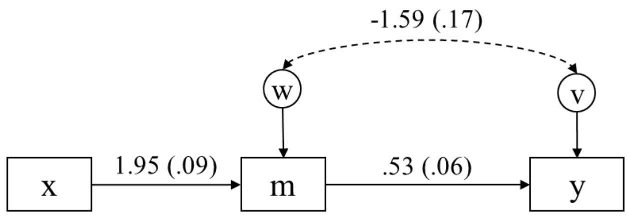
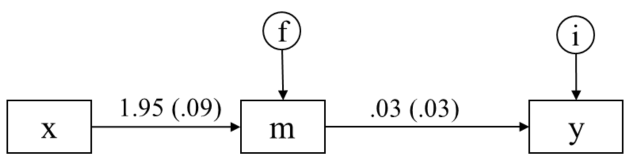
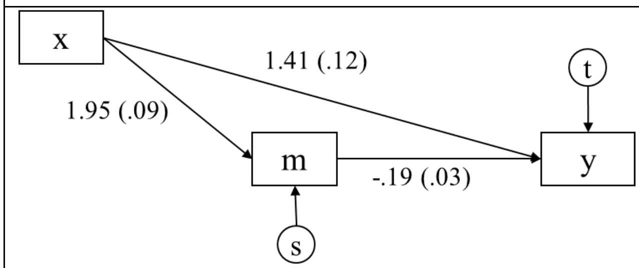
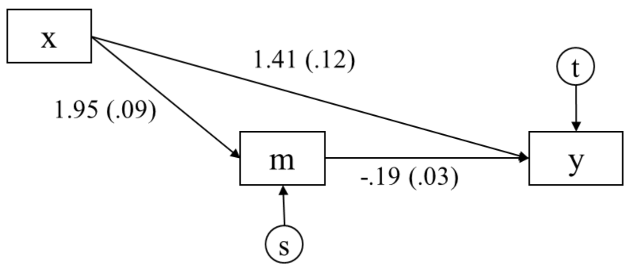
Here I will demonstrate in practice, how the estimator works. Assume the following dataset and correlation matrix on the below diagonal (n = 1,000); underlined entries are the variance-covariance matrix on the top diagonal:

	Mean	Std. Dev.	x	q	m	y
x	0.522	0.500	0.250	-0.014	0.488	0.261
q	10.000	1.037	-0.027	1.075	1.045	-1.071
m	11.022	1.780	0.549	0.566	3.169	0.098
y	5.509	1.659	0.314	-0.623	0.033	2.753

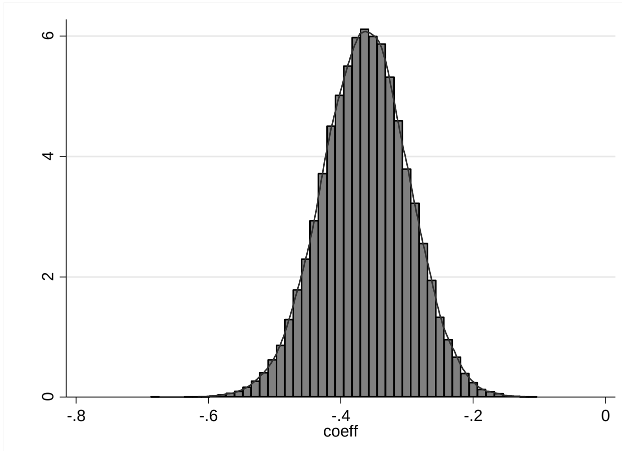
The data can be downloaded here: http://www.hec.unil.ch/jantonakis/siop2015mediation.xlsx

The exogenous variables and disturbances are all normally distributed. Note some have mentioned that the product of the coefficients of two variables (i.e., for testing the significance of an indirect effect) may not be normally distributed and have thus suggested that the indirect effect be bootstrapped (Preacher & Hayes, 2004). In some situations, bootstrapping may make some difference to the *SE's* as compared to using the observed information matrix or a robust estimate of the variance. However, in addition to ignoring the endogeneity problem in mediation, Preacher and Hayes (2004) make a critical error in implementing the bootstrap procedure, as discussed next.

Included below is the true model, as well as different estimated models. I list estimates with SEs in parentheses:

	<u>True model</u> (for data generation) The indirect effect is thus 2.00*.50 = 1.00. For estimation we will omit q.
	<u>Estimated model 1:</u> The estimate of *m* on *y* should be: $$\frac{Cov(y,x)}{Cov(m,x)} = \frac{0.261}{0.488} = .53$$ Using ML and an instrumental variable estimate gives the estimated parameters as depicted on the left, and an indirect effect is 1.95*.53 = 1.04, *SE* =.10, *z* = 10.47, $p < .001$. The negative covariance between the disturbances is the Hausman (1978) testing, indicating the *m* is endogenous and needs to be instrument. Note, 2SLS gives the same result.
	<u>Estimated model 2:</u> Full mediation model using ML. The estimate of *m* on *y* is quite off as is the indirect effect: .06 (ns). In addition, the chi-square test of fit is significant, $\chi^2(1) = 134.12$, $p < .001$, indicating that a constraint made, (i.e. ,*cov*(f,i) = 0) is not consistent with the data. Unfortunately, applied researchers usually release the constraint that *x* does not affect *y* directly, leading to Model 3, which is also wrong.
	<u>Estimated model 3:</u> Partial mediation model using ML. Estimates are rather off. The indirect effect of *x* on *y* is -.3627, *SE* = .0667, *z* = 5.44, $p < .001$. The Baron and Kenny method gives the same point estimate for the indirect effect (-.3627) with an SE = .0668 and *z* = 5.43 (Sobel, 1982).
	<u>Estimated model 4:</u> Partial mediation model estimated using SPSS PROCESS v2.13. Bootstrapped estimate (*k* = 50,000 replications) = -.3627, Bootstrapped *SE* = .0657, and Bootstrapped LLCI = -.4962 and ULCI = -.2383. My replication of their bootstrapping procedure using a program I wrote for Stata gives an estimate of -.3626, Bootstrapped *SE* = .0654, and Bootstrapped LLCI = -.4920 and ULCI = -.2355. Apart from the *SE's*, these estimates are completely off and not much different from those of Model 3.

As for the bootstrapping procedures suggested by Preacher and Hayes (2004), my replication of their program using Stata gives pretty nice looking normal curve for the bootstrapped samples, as indicated by the histogram with the overlaid Kernel density estimate:



However, apart from the problem that the coefficient is completely off, a mistake made by Preacher and Hayes is to suggest to researchers to report the mean of the bootstrap sample for the coefficient (which is what PROCESS reports). In fact, the inventors of the bootstrap mentioned that such bias correction is "dangerous to use in practice" (Efron & Tibshirani, 1994); the reason for this position is rather technical and has to do with the fact that mean of the bootstrap samples is more noisy (i.e., has a higher variance) than the observed estimate.

Conclusions and questions (10 minutes)

To finish, I will recap about the problem of endogeneity in mediation, and briefly note that this problem also exists in situations where field data are being examined particularly too if the modelled independent variable *x* is not exogenous. I will conclude by making suggestions about which software should be used to estimate such models when using SEM (e.g., MPlus, Lisrel, Stata, R) or regression methods (Stata, R, SAS).

I will then take some questions from the floor.

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APPENDIX 1

VITA – JOHN ANTONAKIS

VITA SUMMARY

John Antonakis is of Swiss, Greek, and South-African nationality. He is Professor of Organizational Behavior in the Faculty of Business and Economics of the University of Lausanne, Switzerland, where he has previously served as Associate Dean of Faculty and Research and currently serves as Director of the Ph.D. Program in Management. He received his Ph.D. from Walden University in Applied Management and Decision Sciences (specializing in psychometrics of leadership). He was a postdoctoral fellow in the Department of Psychology at Yale University (focusing on leader development and expertise). Professor Antonakis' research is currently focused on leadership development, power, personality, psychometric assessment, and research methods.

He frequently consults and provides talks, trainings, and workshops to organizations on leadership and human resources issues. His clients have included organizations in various sectors including major banks (e.g., Cantonal Bank of Geneva, Credit Suisse, GE Money Bank), private firms (e.g., INFOSYS, Eli Lilly, Firmenich, Friends Provident, Gunnebo, Kempinski Hotels, Swisscom), government organizations (e.g., European Commission, Federal Department of Finance of the Swiss Confederation, Federal Department of Foreign Affairs of the Swiss Confederation), international organizations (e.g., International Committee of the Red Cross, United Nations Organization), and athletics organizations (e.g., European Athletics Association, International Table Tennis Federation).

He has published in prestigious academic journals such as *Science*, *Psychological Science*, *Academy of Management Journal*, *Intelligence*, *The Leadership Quarterly*, *Journal of Operations Management*, *Journal of Management*, *Harvard Business Review*, *Personality and Individual Differences*, *Academy of Management Learning and Education*, *Organizational Research Methods*, among others. He has also published two books: The *Nature of Leadership* (two editions), and *Being There Even When You Are Not: Leading Through Strategy, Structures, and Systems*. He has been awarded or directed research funds totaling over Sfr 1.9 million (more than $2 million).

Professor Antonakis is associate editor of *The Leadership Quarterly* (and incoming senior editor from 2017) and *Organizational Research Methods*, and is on the boards of several top academic journals including the *Academy of Management Review*, and the *Journal of Management*. He is a member of several professional associations including the Society of Industrial and Organizational Psychology, and the Association for Psychological Science. His research is regularly quoted in the international media (press, and radio) and has been showcased on political and science-based TV shows.

Professor Antonakis is very passionate about communicating science to a broader audience in easy-to-understand ways. To that end, he has featured in several highly-viewed podcasts on topics such as endogeneity (https://youtu.be/dLuTjoYmfXs), charisma (https://youtu.be/SEDvD1IICfE), leader corruption (https://youtu.be/JoLLPNZLBAo), and many others.

APPENDIX 2

CURRICULUM VITAE – JOHN ANTONAKIS