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Third Variable Effects in Management Studies

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The article's aim is to explain the third variable effects in management studies –mediation, suppression, and confounding. Examples of these three types of the third variable effects are based on the European Social Survey (2012) data. It is analyzed whether organizational power is directly related to job satisfaction (example of mediation effect), whether gender predicts a higher perceived social status (example of confounding), and whether job satisfaction increases with age (example of suppression). Consequences for organization and management studies are discussed.

Keywords: confounding, suppression, mediation, organization and management studies, European Social Survey.

Efekty trzeciej zmiennej w naukach o zarządzaniu

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Celem artykułu jest wyjaśnienie wpływu trzeciej zmiennej w naukach o zarządzaniu – mediacji, supresji i zmiennej zakłócającej. Przykłady tych trzech rodzajów efektów bazują na danych pochodzących z Europejskiego Sondażu Społecznego (2012). Analizom poddany jest związek pomiędzy władzą w organizacji a satysfakcją z pracy (przykład efektu mediacji), płcią i postrzeganym statusem społecznym (przykład występowania zmiennej zakłócającej) oraz wiekiem i satysfakcją z pracy (przykład supresji). Dyskutowane są konsekwencje występowania omawianych efektów dla nauk o organizacji i zarządzaniu.

Słowa kluczowe: zmienna zakłócająca, supresja, mediacja, nauki o organizacji i zarządzaniu, Europejski Sondaż Społeczny.

JEL: C18

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The relations discovered in social sciences are rarely (if ever) straightforward. Learning that having power over others promotes corruption (Bendahan, Zehnder, Pralong & Antonakis, 2015) does not allow us to expect every powerful person to behave in an unethical manner. Other studies showed that there are variables that moderate (modify) this relationship – the level of testosterone (Bendahan et al., 2015), moral identity (DeCelles, DeRue, Margolis & Ceranic, 2012), or individuals' propensity to define themselves through their relationships with others (Blader & Chen, 2012).

Due to the complicated nature of human-derived data, the third variable effects are found everywhere, sometimes obscuring the true relationships between studied variables. The third variable effects, showing the conditions that inhibit or facilitate effects of interest, may also help us to better understand the studied phenomena and show not only that they exist, but also the mechanisms (*how?*) and the conditions (*when?*) under which they do or do not (Hayes, 2013). The current article's aim is to clarify and provide examples of various third variable effects, focusing on examples relevant to management studies.

Types of third variables effects

Those who have even occasionally performed an ordinary least squares multiple regression analysis know that the introduction of a second predictor into the model, accompanied by the initial predictor of interest, will usually result in changes in regression coefficients, standard errors, significance test values, and *p*-values. The change would depend on the level of correlation between the introduced predictors, and might result in diminished, enhanced, or even reversed sign of the original relationship (Ludlow & Klein, 2014). In the conceptual model containing an independent variable (X), a dependent variable (Y), and a third variable, the last one could be: a moderator (M), a confounder (C), or a suppressor (S), or a covariate (Co).

Mediation

Mediation (sometimes called an indirect effect, intermediate effect, or surrogate effect) is based on the assumption that the relationship between two variables (X and Y) is established through some sequence of events in which X influences an intermediary variable (M), which then carries its effect further to the ultimate outcome (affect variable Y; see Figure 1). On the graph, the c' path signifies the direct effect between X and Y, when M is controlled for, while ab path (or $c-c'$) signifies the indirect effect of X on Y, through the mediator M. Together, indirect and direct effects account for the total effect ($c = c' + ab$).

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Mediation answers the question of *how* the effect works or *why* does the variable X affect variable Y in an observed manner. Of course, the simplest mediation models that include only single mediators often oversimplify complex relationships, but may still explain them better than two-variable models.

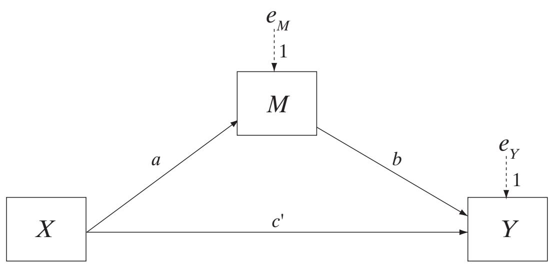

Fig. 1. A diagram of the simple mediation model. Source: Hayes, 2013.

Mediation model needs to be based on theoretical grounds and can take on two forms:

- M is fully responsible for the relationship between X (predictor) and Y (criterion);
- M mediates the relationship between X and Y, but X continues to also directly influence Y.

Importantly, it is now commonly agreed among statisticians that the total effect (c) between Y and X variables does not need to be significant in order to test a theoretically sound mediation (e.g., Hayes, 2009; Shrout & Bolger, 2002). The reason for this is that a significance test may indicate that the total effect (c) is not significant simply because the test is underpowered (small sample size), the assumptions of inferential tests are violated, or there are additional mediators that work in opposite directions, resulting in a total effect of zero (Preacher & Selig, 2012).

It is crucial to remember that mediation analysis is a test of a causal hypothesis, not of a simple correlation (Baron & Kenny, 1986; Dearing & Hamilton, 2006; MacKinnon, Krull & Lockwood, 2000). For this reason, it is best performed on experimental data, which guarantee that the direction of the relationships is known. However, it may also be reasonably tested in instances when it would be impossible to expect the reversed relationship, when we are dealing with longitudinal data, and when we have some serious theoretical grounds to assume a certain direction of the relationship (Hayes, 2013). This said, it is important to treat the conclusions from such non-experimental investigations (as the one presented in this article) with due caution.

Selected methods used to test mediation models

Bootstrapping method relies on taking a large number of random samples of the data with replacement (e.g., 5000), estimating the indirect effect in each sample, and generating a sampling distribution, correcting for bias. A confidence interval for the bootstrapped indirect effect is then defined. If zero is not in the interval, then the indirect effect is different from zero (significant).

One of the most available and well-developed ways to use this method is with the PROCESS macro for SPSS and SAS (Hayes, 2016). PROCESS may be used to estimate direct and indirect effects in mediator models with single and multiple mediators, two and three way interactions in moderation models, or more complicated models, for example those involving conditional indirect effects in moderated mediation models with single or multiple mediators and moderators. The macro can be downloaded from *www.processmacro.org* website.

Monte Carlo Method for Assessing Mediation[1] (Preacher & Selig, 2012) is especially useful when original data is not available and one has to rely on previously computed regression coefficients, but it can also be used on original data. It is relatively easy to perform, even for those not interested in the technicalities that stand behind this method. Two regression analyses need to be performed (or appropriate coefficients obtained) with:

1) independent variable (*X*) as a predictor variable and mediator (*M*) as a dependent variable,
2) *X* and *M* as predictor variables and Y as a dependent variable,

and the appropriate statistics entered the into the mediation calculator available on the following webpage: http://quantpsy.org/medmc/medmc.htm (also see Preacher & Selig, 2012 for additional information). The applet generates R code, which can be submitted to R Statistical Software or Rweb, in order to estimate a confidence interval for the indirect effect. The obtained confidence interval then needs to be examined to see if it contains a value of 0. If yes, the indirect effect is not significant; if not, the indirect effect is significant – we can speak of a mediation effect.

Sobel test (Sobel, 1982) is another easy and widely recognized, but also often criticized (e.g., Zhao, Lynch, Chen, 2010) test for mediation. As for the Monte Carlo method, two regression analyses need to be performed (see above) and the obtained statistics entered into an applet available on the following webpage: http://quantpsy.org/sobel/sobel.htm. The applet provides the results (test statistics, standard errors, and the *p*-values) of three versions of the Sobel test – Sobel, Aroian, and Goodman – which differ slightly in terms of formulas, but all provide easily understandable information on the existence of mediation. This method, although not recommended by some statisticians, is the easiest and the most accessible, hence may be used when performing first steps in the realm of mediation analysis.

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Mediation example: Organizational power and job satisfaction

Experimental studies showed that power increases the level of mood among participants (which might be related to the activation of the approach system; Anderson & Galinsky, 2006; Fast, Gruenfeld, Sivanathan & Galinsky, 2009; Keltner, Gruenfeld, & Anderson, 2003). Since, due to greater power, managers and supervisors should experience more positive mood, it is reasonable to expect that they also experience greater job satisfaction than employees who do not have power over others. If this is the case, can we say that an increase in job satisfaction is directly caused by having power, or maybe it is affected by other factors that often result from higher organizational power, such as financial satisfaction or social status?

In order to check whether supervising others (organizational power) predicts higher job satisfaction, an analysis was performed on the European Social Survey data (2012), where respondents were asked to indicate, among others, their position at work, level of financial satisfaction of the household, perceived social status, feeling of meaningfulness and control at work, and the level of job satisfaction. The following hypothesis was formulated:

Supervisors declare higher job satisfaction than non-supervisors. This difference is mediated by social status.

Method

Respondents. Analyses were performed on the sixth round of the European Social Survey (2012) data for Poland. Because we were only interested in the respondents who were employed at the time of the study, only respondents:
– at the working age (18–70),
– who declared that they are currently employed ["*I am in paid work (or away temporarily) (employee, self-employed, or working for your family business)*"],
were included in the analyzed sample.

For this reason, data from 947 respondents was analyzed (45.2% women), age: 18–70 years old ($M = 40.71$; $SD = 11.72$), including:
- 225 supervisors (35.1% women), age: 19–68 ($M = 42.92$; $SD = 10.69$);
- 716 non-supervisors (48.5% women), age: 18–70 ($M = 40.03$; $SD = 11.6$).

Six respondents (33.3% women) did not report whether they supervise others at work (age: 22–58; $M = 38.67$; $SD = 10.65$).

Variables

a) Supervising others. Item "*Are you responsible for supervising others?*" (coded as 1 – no, 2 – yes).

b) Job satisfaction. Item "How satisfied with job" included in the ESS. Response scale from 0: extremely dissatisfied to 10: extremely satisfied.

c) Social status. Item measures perception of one's current position in society. Item wording: "*There are people who tend to be towards the top of our society and people who tend to be towards the bottom. On this card there is a scale that runs from top to bottom. Where would you place yourself on this scale nowadays*?" Response scale from 0 - bottom of our society to 10 - top of our society.

d) Socio-demographic variables: *Age, Gender (*1 = males, 2 = females), *Education* (in years), *Living with partner* (1 = no, 2 = yes).

e) Satisfaction with household income. Item "*Which of the descriptions comes closest to how you feel about your household's income nowadays?".* Response scale: 1: Very difficult on present income; 2: Difficult on present income; 3: Coping on present income; 4: Living comfortably on present income[2].

f) Health. Item: "*How is your health in general?"* Scale from 1 = very bad to 5 = very good).

Living with partner and subjective health were included due to a known relationship with emotional well-being (e.g., Dush, 2005).

Results and discussion

In order to verify the hypothesis, a hierarchical regression analysis was performed in which job satisfaction was predicted by:

1) supervising others in the first step;
2) supervising others, health, and sociodemographic and socioeconomic variables in the second step;
3) supervising others, health, and sociodemographic and socioeconomic variables, social status, and job control in the third step.

Each step significantly increased the level of explained variance, which increased from $R^2_a = .02$ in the first model [$F(1,911) = 21.61$; $p < .001$] to $R^2_a = .13$ in the fourth model [$F(9,903) = 15.44$; $p < .001$].

As can be seen in Table 1, *X* [supervising others] **significantly predicts *Y*** [job satisfaction], and continues to do so after sociodemographic and socioeconomic variables are added. However, **after adding** social status and job control to the third model, ***X*** [supervising others] **becomes a non-significant** ($p > .05$) predictor of Y. It is a sign that we might be dealing with a mediation effect.

As job satisfaction is related to perceived social status (e.g., Anderson & Brion, 2014; Furnham, Eracleous & Chamorro-Premuzic, 2009), and having organizational power is associated with a higher social status relative to other employees, we might test the following mediation effect: supervising others (having organizational power) causes an increase in subjective social status, which – in turn – causes increased job satisfaction[3]. We may not

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safely assume that perceived job control follows a causal indirect path from organizational power to job satisfaction (it is possible to imagine managers who do not feel that they can influence organizational decisions), thus I will abstain from performing a mediation analysis for this variable.

Predictor	Step 1		Step 2		Step 3	
	b	*p*	*b*	*p*	*b*	*p*
Supervising others	**.73**	**< .001**	**.57**	**< .001**	**.36**	**.03**
Age			.01	.12	.01	.31
Gender			.35	.01	.31	.02
Education in years			–.04	.06	–.07	.01
Living with partner			.35	.02	.33	.03
Health			.43	< .001	.43	< .001
Satisfaction with h. income			.61	< .001	.39	< .01
Social status					.23	< .001
Job control					.07	< .01
Adjusted R^2	.02		.09		.13	
R^2 - change (*p*)	.02 (< .001)		.07 (< .001)		.04 (< .001)	

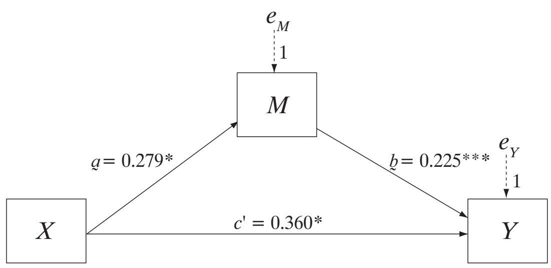
Tab. 1. Hierarchical regression analysis for job satisfaction

Mediation analysis. In order to check whether mediation occurred, a PROCESS macro (Hayes, 2013) was used in which supervising others was included as an independent variable, job satisfaction as a dependent variable, social status as a proposed mediator, and sex, years of education, age, health, satisfaction with household income, job control, and living with partner as control variables. The results of the mediation analysis are provided in Figure 2 and Table 2 and show a significant indirect effect of supervising others on job satisfaction through social status.

Antecedent	Consequent					
	***M* (social status)**			***Y* (job satisfaction)**		
	Coeff.	*SE*	*CI (95%)*	*Coeff.*	*SE*	CI (95%)
X (organizational power)	.279	.131	.0229–0.5355	.360	.165	.0377–.6832
M (social status)	–	–	–	.225	.042	.1426–.3066
Constant	1.237	.524	.2095–2.2645	2.386	.660	1.0909–3.6806
	$R^2 = .121$ $F(8,904) = 15.584$, $p < .001$			$R^2 = .133$ $F(9,903) = 15.440$, $p < .001$		

Notes: * based on 5000 resamples

*Table 2. Model coefficients (unstandardized)**



Notes: *$p < .05$; ***$p < .001$

Fig. 2. Unstandardized regression coefficients for the relationship between supervising others and job satisfaction as mediated by social status, controlled for sex, education, age, health, living with a partner, satisfaction with household income, and job control

To summarize, the mediation analysis confirmed that supervising others (organizational power) indirectly affected job satisfaction through its effect on social status (see Figure 2 and Table 2). Participants who performed supervisory functions in the organization were more likely to report higher social status ($a = .28$) and those who reported higher social status expressed higher job satisfaction ($b = .23$). A bias-corrected bootstrap confidence interval for the indirect effect ($ab = .063$) based on 10,000 bootstrap samples was entirely above zero (.0102 to .1341), confirming its significance. The direct effect ($c' = .360$, 95% CI .0377 to .6832) continued to be significant, suggesting that supervising others influences job satisfaction independent of its effect on social status, possibly through some other untested mediator.

Confounding

A confounder is a variable that is related to independent and dependent variables that obscures or falsely accentuates the relationship between them (Meinert, 1986). Mediators and confounders are impossible to distinguish on statistical bases (MacKinnon, Krull, & Lockwood, 2000). The difference lies in the direction of effects. Mediators are characterized by lying on the causal, unidirectional pathway between exposure and outcome. Confounders are related to, or affect, both exposure and outcome (Figure 3). For this reason, if we fail to include a confounder in a model, the actually nonexistent relationship between predictor and criterion variables might appear (spurious correlation), or a true relationship might be hidden.

If we are dealing with a single confounder, adjustment for the confounder (its inclusion in the regression model) provides an undistorted estimate of the relationship between the independent and dependent variables. The initial relationship between X and Y is usually reduced after the confounder is added because the third variable removes distortion due to the confounding variable.

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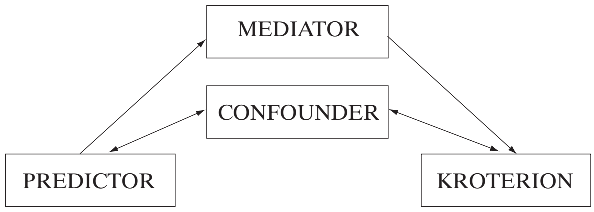

Fig. 3. Differences between mediators and confounders

One of the examples of confounding (MacKinnon et al., 2000) is the positive relationship between annual income and cancer incidence. Because of seniority, older people are likely to earn more money than younger people and they are also more likely to get cancer. Age correlates positively with X and Y and falsely accentuates the relationship between them.

Confounding example. Is the perceived status in the society of women higher than the status of men?

The following simple example shows how confounding can cause an unreal relationship between two variables to appear, here between gender and perceived social status.

Method

Respondents. See mediation example.
Variables. Gender, social status, education (in years).

Results and discussion

A hierarchical regression analysis predicting declared social status was performed – gender was added as the only predictor in the first step, gender and education level (in years) were added in the second step (Table 3).

In the first model, gender significantly predicted social status, indicating that women declare higher status than men, $F(1{,}934) = 6.451$; $p = .011$. However, the introduction of education into the second model caused gender to become a non-significant predictor of social status, $F(1{,}933) = 26.829$; $p < .001$.

Predictor	Step 1		Step 2	
	Beta	*p*	*Beta*	*p*
Gender	.083	.011	.052	.105
Education			.220	< .001
Adjusted R^2	.006		.052	
R^2 – change (p)	.007 (.011)		.048 (< .001)	

Tab. 3. Hierarchical regression analysis for perceived social status

The level of education is related with higher social status. Because women tend to be better educated than men, a failure to include education into the model falsely accentuated the relationship between gender and social status.

Suppression

Another type of third variable effect is called suppression – a situation in which the magnitude of the relationship between an independent variable and a dependent variable becomes larger when a third variable is included in the model (Tzelgov & Henik, 1991).

There are three types of suppression effects.

1. Classical suppression occurs when a non-significant predictor variable becomes significant when a third variable is introduced.
2. Negative suppression occurs when an introduction of a third variable changes the sign of the relation between the predictor and the criterion variables.
3. Reciprocal suppression occurs when a significant relation between predictor and criterion variables becomes enhanced after a third variable is introduced.

Suppression may be analyzed in the context of both mediation and confounding. A suppressor may also be correlated only with predictor variable/s, but not with the criterion variable (e.g., Ludlow & Klein, 2014). In the context of mediation, suppression means that the direct and mediated effects of a predictor on a criterion variable have opposite signs (Cliff & Earleywine, 1994; Tzelgov & Henik, 1991). Such models are also known as inconsistent mediation models (Davis, 1985), in contrast to consistent mediation models, in which the direct and mediated effects have the same sign. If the direct effect of a predictor on the criterion variable is positive, while the indirect effect through the mediator is negative, these two effects may cancel each other out, resulting in a total effect equal to zero (McFatter, 1979). An example of such a situation is presented below.

Suppression example. Does job satisfaction increase with age?

Studies show that older people are likely to experience more positive affect and satisfaction with various areas of their life – including job satisfaction (Herzog & Rodgers, 1981). On the other hand, some studies fail to notice a significant relationship between age and job satisfaction (Bernal, Snyder & McDaniel, 1998). Notably, Bernal et al. (1998) failed to include health as one of the predictors in their model. Knowing that subjective health explains a large proportion of variance in the experienced level of well-being (e.g., Angner et al., 2012), may we suspect that health is a suppressor of the relationship between age and job satisfaction?

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Method

Respondents. See mediation example.
Variables. Job satisfaction, subjective health, job satisfaction (for item wording see method section for the mediation example).

Results and discussion

A hierarchical regression analysis predicting the declared level of job satisfaction was performed – age was added as the only predictor in the first step, age and subjective level of health were added in the second step (Table 4).

Predictor	Step 1		Step 2	
	Beta	*p*	*Beta*	*p*
Age	.035	.283	.098	.004
Health			–.192	< .001
Adjusted R^2	.001		.090	
R^2 – change (*p*)	.001 (.283)		.033 (< .001)	

Tab. 4. Hierarchical regression analysis for job satisfaction

The first model was not significant, $F(1,934) = 1.156$; $p = .283$, and age did not significantly predict the level of job satisfaction. However, the introduction of health into the second model not only resulted in its overall significance, $F(1,933) = 16,412$; $p < .001$, but also increased the magnitude of the relationship between age and job satisfaction (from $\beta = .035$ to $\beta = .098$). Such results suggest that we are dealing with a classical suppression effect, possibly in the form of inconsistent mediation.

The direct effect between age and job satisfaction is positive, but because age is usually related to a decrease in the level of health, which in turn negatively affects satisfaction ratings with many areas of life (including job satisfaction), the indirect and direct effects cancel each other out. Inclusion of both of these variables in the model allows to clear out the part of the variance between age and job satisfaction that is explained by age related changes in health and was obscuring the relationship in the first model.

Conclusion

The current article provided information and examples of the most common third variable effects – mediation, suppression, and confounding. Concentration on the main effects and simple two-variable relationships may results in erroneous conclusions and/or loss of important information, which would otherwise allow us to better predict human behavior. A large portion of studies in the area of organization and management studies is performed using correlational methods, which are highly prone to errors stemming from third variable effects. For this reason carefulness in preparation of the studies, their analysis, and conclusion forming is highly advised, together with – if possible – an attempt to use experimental research methods. Fortunately, the meaning of contingencies and conditions under which the relationships exist seem to gain more attention among social scientists, accompanied by the development of easier and more informative statistical tools (e.g., Hayes, 2013).

Endnotes

1 This method, although performs slightly worse than the bias-corrected bootstrap method, is preferred over the still often used Sobel test of mediation (Sobel, 1982), while being equally easy to perform.

2 The 6th round of ESS does not contain any question on respondent's individual income.

3 Some researchers suggest that social status is a mediator of the effects of organizational power on other variables (e.g., Anderson & Brion, 2014; Willer et al., 2012) and, what is more, some claim that higher social status increases employee's chance to be promoted, reversing the direction of the relationship. For this reason the model proposed here should be treated with great caution and the actual causality should be further verified experimentally.

References

Anderson, C. & Brion, S. (2014). Perspectives on power in organizations. *Annual Review of Organizational Psychology and Organizational Behavior, 1,* 67–97.

Anderson, C. & Galinsky, A.D. (2006). Power, optimism, and risk-taking. *European Journal of Social Psychology, 36,* 511–536.

Angner, E., Ghandhi, J., Purvis, K.W., Amante, D. & Allison, J. (2012). Daily Functioning, health status, and happiness in older adults. *Journal of Happiness Studies*, *14*, 1563–1574, doi: 10.1007/s10902-012-9395-6.

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.

Bendahan, S., Zehnder, C., Pralong, F. & Antonakis, J. (2015). Leader corruption depends on power and testosterone. *The Leadership Quarterly*, *26,* 101–122, doi: 10.26/j.leaqua.2014.07.010.

Bernal, D., Snyder, D. & McDaniel, M. (1998). The age and job satisfaction relationship: Does its shape and strength still evade us? *Journal of Gerontology: Psychological Sciences, 3B,* P287–P293.

Blader, S.L. & Chen, Y.R. (2012). Differentiating the effects of status and power: A justice perspective. *Journal of Personality and Social Psychology, 102,* 994–1014.

Cliff, N. & Earleywine, M. (1994). *All predictors are 'mediators' unless the other predictor is a 'suppressor'.* Unpublished manuscript, University of Sauthern California.

Davis, M.D. (1985). The logic of causal order. In: J.L. Sullivan & R.G. Niemi (Eds), *Sage university paper series on quantitative applications in the social sciences.* Beverly Hills: Sage Publications.

 DOI 10.7172/1644-9584.60.9

Dearing, E. & Hamilton, L.C. (2006). Contemporary advances and classic advice for analyzing mediating and moderating variables. *Monographs of the Society for Research in Child Development*, *71*, 88–104.

DeCelles, K.A., DeRue, D.S., Margolis, J.D. & Ceranic, T.L. (2012). Does power corrupt or enable? When and why power facilitates self-interested behavior. *Journal of Applied Psychology*, *97,* 681–689.

Dush, C.M.K. (2005). Consequences of relationship status and quality for subjective well-being. *Journal of Social and Personal Relationships*, *22*, 607–627.

Fast, N.J., Gruenfeld, D.H., Sivanathan, N. & Galinsky, A.D. (2009). Illusory control: A generative force behind power's far-reaching effects. *Psychological Science*, *20*, 502–508.

Furnham, A., Eracleous, A. & Chamorro-Premuzic, T. (2009). Personality, motivation and job satisfaction: Hertzberg meets the Big Five. *Journal of Managerial Psychology, 24,* 765–779.

Hayes, A.F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* New York, NY: Guilford.

Hayes, A.F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs*, *76,* 408–420.

Herzog, A. & Rodgers, W. (1981). Age and Satisfaction. *Research on Aging, 3*, 142–165.

Keltner, D., Gruenfeld, D.H. & Anderson, C. (2003). Power, approach, and inhibition. *Psychological Review*, *110*, 265–284.

Ludlow, L. & Klein, K. (2014). Suppressor variables: The difference between "is" vesrus "acting as". *Journal of Statistics Education, 22,* 1–28.

McFatter, R.M. (1979). The use of structural equation models in interpreting regression equations including suppressor and enhancer variables*. Applied Psychological Measurement, 3,* 123–135.

MacKinnon, D.P., Krull, J L. & Lockwood, C.M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prevention Science*, 1, 173–181.

Meinert, C.L. (1986). *Clinical trials*: *Design, conduct, and analysis*. New York: Oxford University Press.

Preacher, K.J. & Selig, J.P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, *6*, 77–98.

Shrout, P.E. & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, *7*, 422–445.

Sobel, M.E. (1986). Some new results on indirect effects and their standard errors in covariance structure. *Sociological Methodology, 16,* 159–186.

Tzelgov, J. & Henik, A. (1991). Suppression situations in psychological research: Definitions, implications, and applications. *Psychological Bulletin, 109,* 524–536.

Willer, R., Youngreen, R., Troyer, L. & Lovaglia, M.J. (2012). How do the powerful attain status? The roots of legitimate power inequalities. *Managerial and Decision Economics*, *33*, 355–67.

Zhao, X., Lynch, J.G., Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research, 37,* 197–206.

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