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Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis

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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-

ically, while the popularity of the Baron-Kenny procedure continues to grow, a small technical literature has grown alongside showing flaws in Baron and Kenny's logic. Points that are now accepted in this literature have not diffused to workbench researchers in psychology or consumer research.

We present a nontechnical tutorial in hope of correcting this deficit. Fitzsimons (2008) and Irwin and McClelland (2001) translated an existing technical literature on moderated regression for practicing consumer researchers. Baron and Kenny translated a mediation test suggested by Judd and Kenny (1981). Similarly, we aim to explain to users of Baron and Kenny's tests how new developments should change how they test for mediation. We add to the modern literature on mediation by presenting a typology of mediation models and a decision tree for establishing, classifying, and interpreting mediation for theory building. We present a step-by-step procedure and sample data for classroom demonstration and practice.

BARON AND KENNY'S TESTS

To establish that an independent variable X affects a distal dependent variable Y through a mediating variable M, as shown in figure 1, Baron and Kenny (1986, 1176) recommend three tests:

> A variable functions as a mediator when it meets the following conditions: (*a*) variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e., Path *a*), (*b*) variations in the mediator significantly account for variations in the dependent variable (i.e., Path *b*), and (*c*) when Paths *a* and *b* are controlled, a previously significant relation between the independent and dependent variables is no longer significant, with the strongest demonstration of mediation occurring when Path *c* is zero.

Note that condition *c* requires a significance test for the "direct" Path *c*. Paths *a*, *b*, and *c* are tested and estimated by equations 1, 2, and 3:

$$M = i_1 + aX + e_1. \tag{1}$$

$$Y = i_2 + c'X + e_2. \tag{2}$$
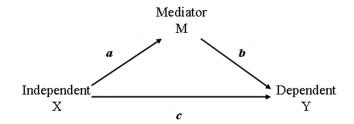
$$Y = i_3 + cX + bM + e_3. \tag{3}$$

Baron and Kenny then state:

> To test mediation, one should estimate the three following regression equations: first, regressing the mediator on the independent variable; second, regressing the dependent variable on the independent variable; and third, regressing the dependent variable on both the independent variable and on the mediator. . . . To establish mediation, the following conditions must hold: First, the independent variable must affect the mediator in the first equation; second, the independent

FIGURE 1

A THREE-VARIABLE NONRECURSIVE CAUSAL MODEL

variable must be shown to affect the dependent variable in the second equation; and third, the mediator must affect the dependent variable in the third equation. (1986, 1177)

Baron and Kenny go on to recommend the Sobel *z*-test for the indirect path $a \times b$ in figure 1, as shown in equation 4:

$$z = \frac{a \times b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}}. \tag{4}$$

Here *a*, *b*, and their squared standard errors come from equations 1 and 3, respectively.

We will dispute three of these points. First, Baron and Kenny claim that mediation is strongest when there is an indirect effect but no direct effect in equation 3. But the strength of mediation should be measured by the size of the indirect effect, not by the lack of the direct effect; the presence of the direct effect can inform theorizing about other mediators. Second, there need not be a significant "effect to be mediated" in equation 2. There should be only one requirement to establish mediation, that the indirect effect $a \times b$ be significant. Other Baron and Kenny tests are useful primarily in classifying the type of the mediation. Third, the Sobel test is low in power compared to a bootstrap test popularized by Preacher and Hayes (2004), in some cases markedly so. Moreover, a researcher expecting a positive indirect effect $a \times b$ may overlook that it can be significant and negative despite positive correlations between X and Y, X and M, and Y and M.

MEDIATORS HIDDEN IN "DIRECT" EFFECTS: BOON TO THEORY BUILDING

Baron and Kenny (1986) asserted that the evidence for mediation is strongest when there is an indirect effect but no direct effect, which they call "full mediation." When there are both indirect and direct effects, they call it "partial mediation." Although full mediation is the gold standard, Iacobucci (2008, 12) notes that, "when all tests are properly conducted and reported, the majority of articles conclude with 'partial mediation.'" That is, mediation is usually accompanied by a direct effect.

Is that a problem for the researcher? The concept of a "direct" effect is clear statistically, but it is often unclear

theoretically. Sometimes there is an a priori theoretical reason to expect a direct effect in addition to an indirect (mediated) effect. For example, a researcher might posit that condom availability (X) has an indirect positive effect on sexually transmitted disease (Y) through perceived risk of sex with multiple partners (M), similar to Bolton, Cohen, and Bloom's (2006) finding that marketing products as remedies creates "get-out-of-jail-free cards." Mapping to figure 1, path a is negative as condom availability reduces perceived risk, and path b is negative as decreased perceived risk increases sex and hence increases disease. Obviously, however, condom availability should reduce disease due to the physical protection by condoms, creating a negative direct path c. Although the mediated path $a \times b$ is positive, it would not undermine the "get out of jail free" theory if perceived risk did not perfectly mediate the effect of condom availability on disease—because of the direct effect c.

More commonly, authors do not hypothesize direct effects a priori. They report them offhand in the "Results" section as evidence of "partial mediation," wherein the $a \times b$ path is significant by a Sobel test and the direct path c is also significant in equation 3. The direct path is simply the "unexplained" part of the X-Y relationship. Although this is sometimes merely an artifact of measurement error in M, we claim that such "direct" paths often result from omission of one or more mediators from the model (Shrout and Bolger 2002).

Mitra and Lynch (1995) showed experimentally that advertising affects price sensitivity through two mediators: (1) it increases consideration set size, which in turn increases price sensitivity, and (2) it increases perceived differences in utility among competing products, decreasing price sensitivity. In such a case, if an investigator hypothesized only the first of these two mediators a priori (advertising → consideration set size → price sensitivity), then the indirect path $a \times b$ would be positive and the unexpected and mislabeled "direct" effect c would be negative. In that case, authors reporting the unexpected negative direct effect can provoke theoretical progress by encouraging researchers reading their paper to search in future work for a second mediation mechanism that is negative in sign.

A good example of this process at work comes from work on "relationship marketing." In one of the most cited marketing articles in the past 15 years, Morgan and Hunt (1994) proposed that relationship marketing activities led to positive business outcomes by increasing trust and commitment. But a meta-analysis by Palmatier et al. (2006) showed that two-thirds of the total effect of relationship marketing on business outcome was direct, not mediated by commitment and trust. The direct effect was positive, leading Palmatier et al. (2009) to look for alternative mediators of the same sign. They found consumer gratitude to be another key mediator.

We conclude, therefore, that there is a silver lining in "partial mediation." The sign of the mysterious "direct" effect has heuristic value for theory building. One might object that the direct effect can reflect the net effect of two or more omitted mediators with different signs. That is

true, but if the net effect is positive (negative), at least one omitted mediator is positive (negative). Look for that first.

NO NEED FOR AN "EFFECT TO BE MEDIATED"

The starting point for Baron and Kenny's (1986) analysis is to establish first that there is a significant zero-order effect of the independent variable X (often an experimental manipulation) on the dependent variable Y in equation 2. This "X-Y test" has been labeled the "effect to be mediated" (Collins, Graham, and Flaherty 1998; Judd and Kenny 1981; Kenny 2003; Kenny, Kashy, and Bolger 1998; Preacher and Hayes 2004). It seems intuitive that, without an effect to be mediated, there is no point in further investigating whether the effect of X on Y is in fact mediated by M. It is for this reason that advisors think they are helping their students by telling them to wait until they have established a zero-order effect of X on Y before hunting for mediation.

This intuition is wrong. There need not be a significant zero-order effect of X on Y, r_{XY}, to establish mediation. What Baron and Kenny (1986) and most users of their tests thereafter have missed is that the zero-order effect of X on Y is in fact mathematically equivalent to the "total effect" of X on Y in figure 1.

$$c' = (a \times b) + c. \qquad (5)$$

That is, it exactly equals the sum of the "indirect path" (path $a \times$ path b, usually hypothesized) and the "direct path" (path c, usually not hypothesized, as just discussed).

If c and $a \times b$ are of the same sign, c' will have the same sign. We call this complementary mediation if both the indirect path $a \times b$ and the direct path c are significant. In such a situation, the X-Y test is superfluous since it will pass any time $a \times b$ and c are significant.

But if c and $a \times b$ are of opposite signs—what we will call competitive mediation if both paths are significant—then c' can be close to zero and the X-Y test may fail. Our earlier examples of "get-out-of-jail-free" condom use and "advertising effects on price sensitivity" match this case. If the direct effect is substantially larger than the indirect effect, as could occur in our condom example, the "effect to be mediated" would appear to be of the wrong sign! Competitive and complementary mediations are equally likely and of equal theoretical interest a priori. Both point to a theoretically interesting indirect effect. Both identify an unexplained direct effect and guide future research to look for alternative mediators that match the sign of the revealed direct effect. It is nonsensical that only complementary mediations should be judged to be publishable, yet this is the consequence of consumer researchers' reliance on Baron and Kenny's X-Y test.

We earlier introduced a hypothetical modification of Mitra and Lynch's (1995) study. Authors had used Baron and Kenny's approach but had anticipated only the positive effect of advertising on price sensitivity through consideration

set size, failing to anticipate the negative effect through perceived differences among competing products. It would not be surprising if r_{XY}, the total effect of advertising on price sensitivity, were not significant here. One can imagine the authors giving the project up after failing to find an "effect to be mediated." They should persist. Reviewers should not point to the unexplained negative direct path to deter publishing findings of a positive indirect path. Authors can tell future researchers in the "Discussion" section of their paper that (*a*) advertising increases consideration set size, which in turn increases price sensitivity; (*b*) despite the progress in the paper, there is room for future work accounting for the direct effect; and (*c*) in searching for added mediators, future authors should focus first on those that would produce a negative indirect path. Such a focused discussion would be considerably more helpful than most "Future Research" sections now published.

The problems we just identified with the *X-Y* test have been recognized in the technical literature on mediation in psychology (Cliff and Earleywine 1994; Collins et al. 1998; Davis 1985; Judd and Kenny 2010; Kenny 2003; Kenny et al. 1998; MacKinnon 2000, 2008, 2009; MacKinnon, Krull, and Lockwood 2000; MacKinnon et al. 2002; McFatter 1979; Shrout and Bolger 2002). The discussion, couched in arcane language about "suppressor effects" in multiple regression, has not migrated to consumer researchers unaware of its relevance to their own widely shared interests in theory building. Up to April 2009, in the *Journal of Consumer Research*, the *Journal of Marketing*, and the *Journal of Marketing Research*, 240 articles cited Baron and Kenny (1986), while five articles cited any of the dissenting or later revisions by Kenny and colleagues.

Next, we present a typology of all possible patterns that a researcher might observe. We explain for each pattern its implications for theory testing and theory building. We present unified criteria for establishing mediation, understanding the particular type of mediation, and translating the data patterns uncovered into theoretical statements.

A TYPOLOGY OF MEDIATIONS AND NONMEDIATIONS

It should be evident by now that the Baron and Kenny classification of full, partial, and no mediation is somewhat coarse and misleading due to a one-dimensional conception of mediation better seen as two-dimensional. In a nonrecursive three-variable causal model, we identify three patterns consistent with mediation and two with nonmediation:

1. *Complementary mediation*: Mediated effect ($a \times b$) and direct effect (c) both exist and point at the same direction.
2. *Competitive mediation*: Mediated effect ($a \times b$) and direct effect (c) both exist and point in opposite directions.
3. *Indirect-only mediation*: Mediated effect ($a \times b$) exists, but no direct effect.
4. *Direct-only nonmediation*: Direct effect (c) exists, but no indirect effect.

5. *No-effect nonmediation*: Neither direct effect nor indirect effect exists.

Our complementary mediation overlaps with Baron and Kenny's partial mediation; our indirect-only mediation overlaps with their full mediation. Our other three categories of competitive mediation, direct-only nonmediation, and no-effect nonmediation were often clubbed together as no mediation by Baron and Kenny—a ticket to the file drawer. Other authors have referred to complementary mediations as "consistent" models or "positive confounding" and to competitive mediations as "inconsistent" models or "negative confounding" (Cliff and Earleywine 1994; Collins et al. 1998; Davis 1985; MacKinnon et al. 2000; McFatter 1979; Shrout and Bolger 2002). Our last two types have rarely been discussed in this literature because the full-partial-no scale assumes one dimension. Proper interpretation of one's data requires two dimensions for the indirect path and the direct path.
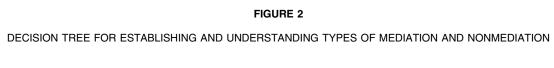
In our approach to mediation analysis, c' now represents only the total effect—not the "effect to be mediated." A significant c' does not necessarily indicate mediation, and a nonsignificant c' does not necessarily indicate lack of mediation. Some authors argue for waiving the *X-Y* test in some situations (Collins et al. 1998; Kenny 2003; MacKinnon et al. 2000; Shrout and Bolger 2002). We maintain that the *X-Y* test is never relevant to establishing mediation. Researchers should not give up on a mediation hypothesis when they fail to find an "effect to be mediated." It may well be possible to establish an indirect effect despite no total effect.
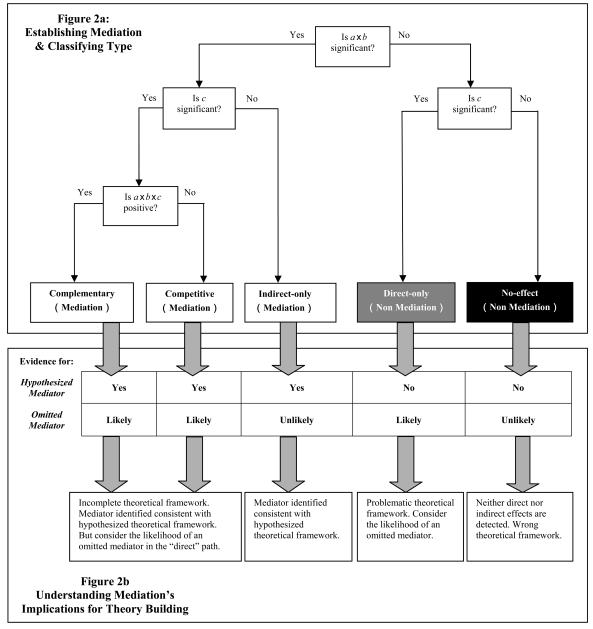
Figure 2 shows a decision tree to conceptualize these five types of mediation and nonmediation to convey to readers what really matters in a mediation analysis. The top of the figure (2*a*) shows the statistical path to establishing mediation and classifying its type. The bottom of the figure (2*b*) shows the interpretation of the data pattern for conclusions about theory.

First, consider establishing mediation. In the top part of figure 2, at the first node, is the indirect path $a \times b$ significant? If the answer is yes, then we have some form of mediation, as is shown on the left of figure 2. To establish mediation, Baron and Kenny's three equations are useful, but this is not because one must pass any of their tests. Regression equations 1 and 3 estimate the parameters a and b used to test the indirect effect. But it is the distribution of their product that matters. The one and only requirement to demonstrate mediation is a significant indirect effect $a \times b$ by a Sobel test, or, as we will explain later, by a superior bootstrap test (Preacher and Hayes 2004, 2008).

The main role for Baron and Kenny's three equations is in deciding the type of mediation. Consider the left half of figure 2, where the indirect path $a \times b$ is significant. If the direct effect c is not significant in equation 3, we have indirect-only mediation. If c is significant, then is the product $a \times b \times c$ positive? The answer will be yes if the indirect path $a \times b$ and direct path c are of the same sign, signaling complementary mediation. The answer will be no if the

DECISION TREE FOR ESTABLISHING AND UNDERSTANDING TYPES OF MEDIATION AND NONMEDIATION

Figure 2a:
Establishing Mediation
& Classifying Type

Figure 2b
Understanding Mediation's
Implications for Theory Building

indirect path $a \times b$ and the direct path c are of opposite signs, signaling competitive mediation.

The bottom half of figure 2 shows the implications for theory. First, in all three cases on the left, the data support the hypothesized mediation story $X \to M \to Y$. This includes competitive mediation, where there may not be a significant treatment effect of X on Y as measured by r_{XY}. Second, for both complementary and competitive mediations, the significant direct effect c points to the possible existence of

some omitted second mediator that can be pursued in future research. The sign of this direct effect gives guidance for the sign of an omitted indirect path.

Now consider the two cases on the right-hand side of figure 2—when the indirect path $a \times b$ is not significant. Only the rightmost path, no effect nonmediation, should be viewed as a failure. This pattern of nonsignificant indirect effect $a \times b$ and nonsignificant direct effect c can occur despite a significant total effect of X on Y, without hints

about the mechanism for the "effect to be mediated." In the case of direct-only nonmediation, there is no indirect effect but a significant direct effect c. This pattern is likely to be viewed as disappointing by authors, but the sign of the direct effect can point to as yet undiscovered mediators.

Our typology and figure have no separate test for the significance of b, contrary to Baron and Kenny's (1986) claim that b must be significant to claim mediation, that is, that there must be a significant partial effect of M when X is in the model. A strong link between X and M can inflate the standard error of b. Finding no significant b is not per se embarrassing to a mediation story, but if b is not significant due to multicollinearity, the indirect effect $a \times b$ necessary for establishing mediation will likely not be significant. This implies that researchers with correct mediation hypotheses may be disappointed by the low power of the test, ironically because of a strong independent variable to mediator connection. We now consider the proper statistical procedure for establishing the indirect effect.

SOBEL'S NOT NOBLE

Baron and Kenny (1986) recommended testing the significance of the indirect path $a \times b$ by the Sobel z-test shown in equation 4 or variants. Equivalently, z tests whether the difference between the total effect and the direct effect is statistically significant.

$$z = \frac{a \times b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}} \tag{4}$$

Preacher and Hayes (2004) made a strong case that it is insufficient to show that the effect of X on Y is reduced in size when M is added to the model. Finding that X has a significant total (zero order) effect on Y in equation 2 and no significant partial effect in equation 3 does not imply a significant difference between the two. Equivalently, it also does not imply a significant indirect effect $a \times b$ in the numerator of equation 4 when measured against the standard error of the indirect path in the denominator. Preacher and Hayes developed easy to use SPSS and SAS macros for calculating Sobel's z, ironically popularizing the Sobel test.

But the main contribution of Preacher and Hayes (2004) was to present SAS and SPSS syntax for an alternative "bootstrap" test of the indirect effect that is almost always more powerful than Sobel's test. Because the indirect effect is the product of two parameters, the sampling distribution of products and Sobel's z is not normal. For a positive indirect path $a \times b$, the sampling distribution is positively skewed, with a shorter, fatter tail to the left—the end of the distribution closer to zero. Sobel's z sets 95% confidence intervals symmetrically around the mean estimates of $a \times b$. This implies that the lower bound of the confidence interval for positive $a \times b$ has less than 2.5% of the true sampling distribution to the left. So the 95% confidence interval will often improperly include zero, compared to the 95% confidence interval we would create if we could observe the sampling distribution of $a \times b$.

The bootstrap test implemented by Preacher and Hayes (2004, 2008) solves that problem by generating an empirical sampling distribution of $a \times b$. It takes the researcher's sample of size N and from it draws with replacement N values of (X, M, Y) to create a new sample. Equations 1 and 3 are estimated for each bootstrap sample, allowing estimation of a, b, and $a \times b$. After, say, 5,000 such bootstrap samples have been drawn and $a \times b$ estimated for each, the SAS and SPSS macros estimate the indirect effect as the mean of these estimates. The bootstrap test actually relies on the 95% confidence intervals from the empirical distribution of $a \times b$ estimates. The lower bound of the 95% confidence interval is at the 2.5% point on this cumulative distribution, and the upper bound of the 95% confidence interval is at the 97.5% point. Preacher and Hayes's macro (2008; see http://www.comm.ohio-state.edu/ahayes/SPSS%20programs/indirect.htm) also accommodates multiple mediators and covariates.

We reanalyze a data set from Zhao (1997) collected during Super Bowl 1994 to show how to perform Preacher-Hayes bootstrap tests in either SAS or SPSS. The unit of analysis is the brand advertised during the Super Bowl broadcast. The dependent variable, *liking*, measures audience rating of a brand's advertisement(s) on a 0–1 scale, where 1 represents maximum liking. The independent variable, *frequency*, is the number of ads a brand placed during the game. The mediating variable, *clutter*, is the total number of other ads in the same commercial breaks where the brand placed its ads. The data are available at http://www.comm.hkbu.edu.hk/zhao/shared. (To produce the output in fig. 3, we revised Preacher and Hayes's script that uses c for total effect and c' for direct effect to be consistent with notation in our article, Baron and Kenny [1986], and most prior work.)

To perform bootstrapping in SPSS, open your data set and then follow the steps below:

i. Open the Preacher-Hayes script in SPSS for Windows (.sbs file).
ii. Run the Preacher-Hayes script from the scripting window to activate the dialog box.
iii. Identify your dependent (i.e., *liking*), independent (*frequency*), and one or more mediating variables (here only *clutter*). You may also identify covariate variables if appropriate.
iv. Set bootstrap samples to, say, 5,000.
v. Set confidence level at 95% or 99%.
vi. Click OK to execute the script.
vii. Find "Bootstrap Results for Indirect Effects" from the output window and the 95% confidence interval ($-.0930$ to $-.0268$ in our case). If the confidence interval does not include 0, the indirect effect $a \times b$ is significant and mediation is established, which takes you to the left of figure 2. If the confidence interval includes 0, $a \times b$ is not significant and mediation hypothesis is rejected, which takes you to the right of figure 2.

FIGURE 3

SPSS OUTPUT FROM PREACHER AND HAYES'S (2008) BOOTSTRAP SCRIPT TESTING INDIRECT EFFECT *a* × *b*

```
Run MATRIX procedure:


Dependent, Independent, and Proposed Mediator Variables:
DV =    liking
IV =    frequenc
MEDS = clutter


Sample size
        56


IV to Mediators (a paths)
            Coeff        se         t         p
clutter    2.5359      .3047    8.3238     .0000


Direct Effects of Mediators on DV (b paths)
            Coeff        se         t         p
clutter    -.0208      .0050   -4.1712     .0001


Total Effect of IV on DV (c prime path)
            Coeff        se         t         p
frequenc    .0043      .0127     .3351     .7389


Direct Effect of IV on DV (c path)
            Coeff        se         t         p
frequenc    .0570      .0169    3.3802     .0014


Model Summary for DV Model
     R-sq  Adj R-sq         F       df1       df2         p
     .2487     .2204    8.7726    2.0000   53.0000     .0005


*********************************************************************

            NORMAL THEORY TESTS FOR INDIRECT EFFECTS


Indirect Effects of IV on DV through Proposed Mediators (ab paths)
            Effect        se         Z         p
TOTAL      -.0527      .0139   -3.7917     .0001
clutter    -.0527      .0139   -3.7917     .0001


*********************************************************************

            BOOTSTRAP RESULTS FOR INDIRECT EFFECTS


Indirect Effects of IV on DV through Proposed Mediators (ab paths)
            Data        boot      Bias        SE
TOTAL      -.0527     -.0526     .0001     .0157
clutter    -.0527     -.0526     .0001     .0157


Bias Corrected and Accelerated Confidence Intervals
            Lower      Upper
TOTAL      -.0930     -.0268
clutter    -.0930     -.0268


*********************************************************************

Level of Confidence for Confidence Intervals:
  95


Number of Bootstrap Resamples:
  5000


------ END MATRIX -----
```

The Preacher-Hayes script allows point-and-click, making it very user friendly. Mac users and researchers who wish to have more control over the process should run Preacher-Hayes syntax instead of following script steps i–vi, then follow step vii to interpret the result. All that is required is to add a line to the end of Preacher and Hayes's syntax to specify *X, M, Y,* and any covariates: "SOBEL y = liking/ x = frequency/m = clutter/boot = 5000." Use bootstrap, not ("Normal Theory") Sobel tests from the output.

RECOMMENDED STEPS FOR MEDIATION ANALYSIS

We recommend that to establish mediation the Baron-Kenny "three tests + Sobel" steps be replaced with one and only one test: the bootstrap test of the indirect effect $a \times b$. In Baron and Kenny's analysis, one runs three regressions using standard software:

$$M = i_1 + aX + e_1. \tag{1}$$

$$Y = i_2 + c'X + e_2. \tag{2}$$

$$Y = i_3 + cX + bM + e_3. \tag{3}$$

We argue that to establish mediation, all that matters is that the indirect effect is significant. Simply run the Preacher-Hayes script and generate "Bootstrap Results for Indirect Effects," as we showed in figure 3, to determine whether the indirect effect $a \times b$ is significant and thus whether to take the left (mediation) or right (nonmediation) branch of figure 2.

Now, classify the type of mediation by estimating the coefficients *a, b,* and *c*. You may use SEM to estimate all parameters simultaneously, or you may run the two regression equations 1 and 3. Or, even easier, Preacher-Hayes script output (fig. 3) provides these estimates automatically under "Direct and Total Effects." The first thing to note is whether the direct effect *c* is significant. It tells you what type of mediation or nonmediation you have:

i. If $a \times b$ is significant but *c* is not, you have indirect-only mediation.
ii. If $a \times b$ is not significant but *c* is, you have direct-only nonmediation.
iii. If neither $a \times b$ nor *c* is significant, you have no effect nonmediation.
iv. If both $a \times b$ and *c* are significant, determine the sign of $a \times b \times c$ by multiplying the three coefficients, or by multiplying *c* by the mean value of $a \times b$ from the bootstrap output. If $a \times b \times c$ is positive, it is complementary mediation; if $a \times b \times c$ is negative, it is competitive mediation.

When reporting the results of the mediation analysis, report the mean value of $a \times b$ and the 95% confidence interval from the bootstrap analysis. Report also the unstandardized regression coefficients *a, b,* and *c* to allow substantive interpretation of the results. In the next section, we describe errors that can occur if authors report only significance levels without attention to the signs of those coefficients and congruence with their theory.

Applying these steps to our Super Bowl example, we found the mean indirect effect from the bootstrap analysis is negative and significant ($a \times b = -.0527$), with a 95% confidence interval excluding zero ($-.0930$ to $-.0268$). In the indirect path, a unit increase in frequency increases clutter by $a = 2.53$ units; $b = -.0208$, so holding constant frequency, a unit increase in clutter reduces liking by .0208 units on a 0 to 1 scale. The direct effect *c* (.057) is also significant ($p = .0014$); holding constant clutter, a unit increase in frequency increases liking by 0.057, perhaps reflecting fluency effects. Since $a \times b \times c$ ($-.0030$) is negative, it is a competitive mediation.

Despite consistency of these findings with the author's theory, when the mediation results from this study were first submitted to a top journal, the paper was rejected on the grounds that the data failed Baron and Kenny's *X-Y* test ($c' = .0043, p = .74$). Other findings (but not the mediation) from the study were later published in another journal (Zhao 1997). As discussed before, the *X-Y* test is about the total effect of *X* on *Y*, that is, the sum of the direct and indirect effects. Here, the indirect and direct effects of roughly equal size and opposite signs canceled each other out. The author might have had a different reception at the first journal had he and reviewers used our steps and our decision tree instead of Baron and Kenny (1986).

UNEXPECTEDLY FLIPPED SIGNS OF INDIRECT PATHS

A researcher hypothesizing a positive indirect effect may follow Baron and Kenny's procedure faithfully and observe all positive zero-order correlations and a significant Sobel or bootstrap test—but of the wrong sign! For example, in a simulation with $r_{XM} = .8$, $r_{MY} = .4$, and $r_{XY} = .6$, the mean indirect effect $a \times b$ was -0.18. It would be easy to miss the fact that, for these values, *b* is negative.

Cohen and Cohen (1975) and Friedman and Wall (2005) note that an indirect effect opposite in sign to the zero-order correlations arises in cases of "net suppression" when all zero order correlations are positive and $r_{XM} > (r_{MY}/r_{XY})$. In standardized variables, $\beta_M = (r_{MY} - r_{XY}r_{XM})/(1 - r_{XM}^2)$ and $\beta_X = (r_{XY} - r_{MY}r_{XM})/(1 - r_{XM}^2)$. The reader can work out that β_M is always negative and β_X is positive for positive correlations satisfying the inequality $r_{XM} > (r_{MY}/r_{XY})$.

These authors did not discuss mediation but rather two correlated causes (X_1 and X_2) that combine additively to create an effect (*Y*), but there are interesting implications of their proofs when the same correlations are used to test a mediation hypothesis. All cases of net suppression in mediation analysis can be seen as special cases of competitive mediation in which the direct path dominates the indirect

path. But unlike the cases we showed before where competitive mediation was not problematic for the author expecting a positive indirect path, this case yields a negative indirect path, contrary to the authors' theory. Casual conversation with colleagues suggests that they look for the significance but not the sign of the indirect effect. To avoid publishing a conclusion that is wrong, authors should report (and be asked by journals to report) the type of mediation and actual a, b, and c coefficients, not just the significance test of the indirect effect.

STRUCTURAL EQUATION MODELS AND BARON AND KENNY'S REGRESSION APPROACH

Iacobucci (2008) argues that structural equation (SEM) approaches dominate the "causal steps" approach of Baron and Kenny (1986). We agree that the SEM approach is superior to Baron and Kenny's because it estimates everything simultaneously instead of assuming that equations 1–3 are independent. However, the greater technical complexity of SEM makes it seem unlikely that SEM will supplant Baron and Kenny's approach soon. This led us to focus in this article on reforming the use of a Baron-Kenny procedure that has a much larger "installed base" of users than SEM.

The reader should understand, however, that our article is not about the particular statistical approach but about conceptual issues in mediation analysis that hold with equal force to SEM and regression analyses. Whether via regression or SEM, only the indirect effect needs to be significant, bootstrap tests should be used to test this effect, the mediation type should be properly classified in the mediation tree in figure 2, and one should consider the sign of unexpected "direct" effect for hints about omitted mediators.

Having said that, there are reasons for learning SEM. First, even if there is no "true" direct effect or omitted second mediator, one can observe a significant direct effect c due to measurement error in the indicator of M (Birnbaum and Mellers 1979). With multiple measures of M, SEM models error in the measurement of the mediator, allowing one to distinguish a "true" direct effect from one that is an artifact of errors in variables in measuring M.

Second, sometimes a researcher's data may seem to conform to Baron and Kenny's conditions for mediation, but the "mediator" is not conceptually different from the independent variable: it is effectively a manipulation check. In other cases, the authors have a mediator M that is effectively an alternative measure of the dependent variable Y. In such cases, the data may seem to conform to Baron and Kenny's criteria, but the mediation analysis is theoretically meaningless. Because it is so common for measured mediators to be single-item scales, it is difficult to show the discriminant validity of the putative "mediator" vis-à-vis the independent variable or dependent variable. When discriminant validity is in doubt, the authors can build a more convincing case by having multi-item scales for the "mediator" to be able to show by confirmatory factor analysis that a one-factor model will not fit either the combined measures of M and Y or the combined measures of a manipulation check for X and M. Armed with these multi-item scales, the authors could forswear Baron and Kenny's regression approach and follow the structural equation approach advocated by Iacobucci (2008). The points in our article all still hold.

CONCLUSION

Baron and Kenny's (1986) framework for mediation analysis has become ubiquitous in the pages of the *Journal of Consumer Research*, as in other social science journals. Statistical literature has disputed some of their points, but this has not affected practice in consumer research. We have simplified these criticisms and added our own, providing an overarching framework that considers two dimensions—the indirect effect and the direct effect—rather than the one-dimensional "full," "partial," and "none" classification employed by Baron and Kenny.

First, although Baron and Kenny and current practice hold up "full mediation" as the gold standard, most studies report "partial mediation" with a significant direct path c. The direct path is rarely predicted or explained. We contend that the unexplained direct path can indicate an omitted mediator. "Future Research" discussions could be more enlightening than most are now if researchers would speculate about the possible meanings of unexpected direct effects and potential omitted indirect paths of the same sign as the direct effect.

Second, we argue that there need not be a significant r_{XY} in a proper mediation analysis. For similar reasons, it is a mistake to advise students to "first just establish an effect (to be mediated)" before starting to think about and test mediation. The only requirement for mediation is that the indirect effect $a \times b$ be significant. Use the tree diagram in figure 2 to determine the type of the mediation and guide the discussion for theoretical implications.

Third, in testing the significance of an indirect effect $a \times b$, use the more rigorous and powerful bootstrap test, not Sobel. When using either of these tests, be alert to the sign of the indirect effect. It is possible to have significant positive correlations between X and M, X and Y, and M and Y and still have a significant negative indirect effect, contrary to one's theory.

We consumer researchers would be better off if we could unlearn some "truths" we learned from Baron and Kenny (1986) in our doctoral programs. Authors might then discover that data that looked discouraging actually support their prior mediation theories, marginal Sobel tests may give way to significant bootstrap tests, and unexplained direct effects may turn from irritation to inspiration.

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CORRECTION.—Since this article was published online on February 15, 2010, a correction has been made. In the second to the last paragraph of the section entitled Recommended Steps for Mediation Analysis, the earlier version read: "Since $a \times b \times c$ ($-.0002$) is negative, it is a competitive mediation"; ($-.0002$) has now been changed to ($-.0030$) in both the online and print versions of the article. Corrected on May 21, 2010.