The True Role that Suppressor Effects Play in Condition-Based Regression Analysis: None. A Reply to Fiedler (2021)

Humberg, Sarah
University of Münster, Germany

Michael Dufner
Witten/Herdecke University, Germany & University of Leipzig, Germany

Felix D. Schönbrodt
Ludwig-Maximilians-Universität München, Germany

Katharina Geukes
University of Münster, Germany

Roos Hutteman
Utrecht University, the Netherlands

Maarten H. W. van Zalk
University of Osnabrück, Germany

Jaap J. A. Denissen
University of Utrecht, the Netherlands

Steffen Nestler
University of Münster, Germany

Mitja D. Back
University of Münster, Germany

This is the final author version (before journal's typesetting and copyediting) of the following article:

Humberg, S., Dufner, M., Schönbrodt, F. D., Geukes, K., Hutteman, R., van Zalk, M. H. W., Denissen, J. J. A., Nestler, S., & Back, M. D. (2022). The true role that suppressor effects play in condition-based regression analysis: None. A reply to Fiedler (2021). *Journal of Personality and Social Psychology, 123*(4), 884–888. https://doi.org/10.1037/pspp0000428

Abstract

Condition-based regression analysis (CRA) is a statistical method for testing self-enhancement (SE) effects. That is, CRA indicates whether, in a set of empirical data, people with higher values on the directed discrepancy S-R (self-view S minus reality criterion R) tend to have higher values on some outcome variable (e.g., happiness). In a critical comment, Fiedler (2021) claims that CRA yields inaccurate conclusions in data with a suppressor effect. Here, we show that Fiedler's critique is unwarranted. All data that are simulated in his comment show a positive association between S-R and H, which is accurately detected by CRA. By construction, CRA indicates an association between S-R and H only when it is present in the data. In contrast to Fiedler's claim, it also yields valid conclusions when the outcome variable is related only to the self-view or when there is a suppressor effect. Our clarifications provide guidance for evaluating Fiedler's comment, clear up with the common heuristic that suppressor effects are always problematic, and assist readers in fully understanding CRA.

Keywords: condition-based regression analysis; self-enhancement; suppressor effect; positivity of self-view

Author Note

Supplemental materials for this article are available at https://osf.io/fbshg/.

Correspondence concerning this article should be sent to Sarah Humberg, University of Münster, Department of Psychology, Fliednerstr. 21, 48149 Münster, Germany. E-Mail: sarah.humberg@wwu.de.

The True Role that Suppressor Effects Play in Condition-Based Regression Analysis: None. A Reply to Fiedler (2021)

In Humberg et al. (2018), we established condition-based regression analysis (CRA) as a statistical method for investigating the (mal)adaptive effects of self-enhancement (SE). Fiedler (2021) claims that CRA yields inaccurate conclusions when a suppressor effect is present in the data. Here, we show that Fiedler's critique is unwarranted.

The Aim and Logic of CRA

For decades, researchers in social and personality psychology have been interested in exploring the consequences of self-enhancement (SE). To this aim, they typically defined the psychological construct SE[1] as the directed discrepancy S-R between people's self-view S and their value on some reality criterion[2] R, and posited an association between SE = S-R and some outcome of interest.

As a concrete example, suppose that Researcher X defines SE as S-R and suggests a positive effect of SE = S-R on people's happiness. Aiming to put her theory to an empirical test, Researcher X translates it into a corresponding expectation about measurable variables: She expects that the higher an individual's value of SE=S-R is, the higher will his/her happiness value H be. That is, she expects that "*people with higher S-R tend to have higher H*"—which we here call "*S-R effect pattern*". CRA is a statistical method that can inform Researcher X whether the expected S-R effect pattern is present in her data. Because an S-R effect pattern is an association between three variables at a time (S, R, H), CRA is based on a

[1] Within this response, we remain consistent with the conceptual and mathematical notation in our paper that introduced CRA (Humberg et al., 2018), which sometimes differs from the terminology that Fiedler used. Whenever we consider it vital to support readers in making the match between our original terminology and his, we provide additional comments in footnotes.
To begin, the definition of SE stated here matches the one in Humberg et al. (2018) and is the definition of SE that implies the applicability of the version of CRA that Fiedler criticizes (see Humberg et al., 2018, for variants of CRA that fit other common definitions of SE). The definition *diverges* from the terminology in Fiedler's comment, where the term "self-enhancement (SE)" labels an expected *association* between the construct SE and happiness and also the result of the statistical index $r_{(S-R)H}$.

[2] Fiedler denotes the reality criterion R as "O". We stick with the original notation from the CRA paper to avoid confusion with the number zero.

model that can mirror such three-dimensional associations:

$$H = c_0 + c_1 S + c_2 R + \varepsilon \quad (1)$$

The CRA method specifies that, after Researcher X has estimated the regression in Equation 1, she can conclude that the data show an S-R effect pattern if the estimated coefficients satisfy two conditions: c_1 must be significantly positive and c_2 must be significantly negative.

Figure 1A shows the data assessed by Researcher X (see osf.io/fbshg for the R code to reproduce all simulated data, plots, and results from this article). Each person's self-rating S, his/her criterion value R, and his/her happiness value H determine the position of his/her dot in the three-dimensional coordinate system. Eyeballing the raw data in Figure 1A shows that people with higher S-R values tend to have higher H: People whose self-view exceeds their criterion value by a lot (e.g., Tom with S=1.4, R=-0.4) tend to be happier than people whose self-view is about accurate (Ann, S=-1.7, R=-1.2), and the latter are happier than people whose self-view is far behind their criterion value (Sam, S=-1.6, R=0.2). CRA correctly supports this visual impression of the trend in the data (see Figure 1C for the graph). The estimated coefficients (c_1=.5, c_2=-.2) satisfy the conditions c_1>0 and c_2<0. That is, the data in Figure 1A show an S-R effect pattern and CRA correctly detects this.

More generally, the *CRA conditions* "c_1>0 and c_2<0" ensure that CRA accurately detects S-R effect patterns in any data that show such a trend. This is because the CRA conditions are a direct translation of the expected pattern into a corresponding statistical representation. When we expect an S-R effect pattern, we expect that, for two individuals with equal R values, the person with the higher self-view S is happier, because he/she is the person with higher SE=S-R. This expectation translates into c_1>0, because the math of multiple regression implies that c_1 is the association between S and H conditional on R (i.e., in a hypothetical subsample of people with the same R). Additionally, we expect that, for two individuals with equal S values, the person with the *lower* R is happier, because he/she is the one with higher SE in this case. The statistical representation is c_2<0, because c_2 is the association between R and H conditional on S.

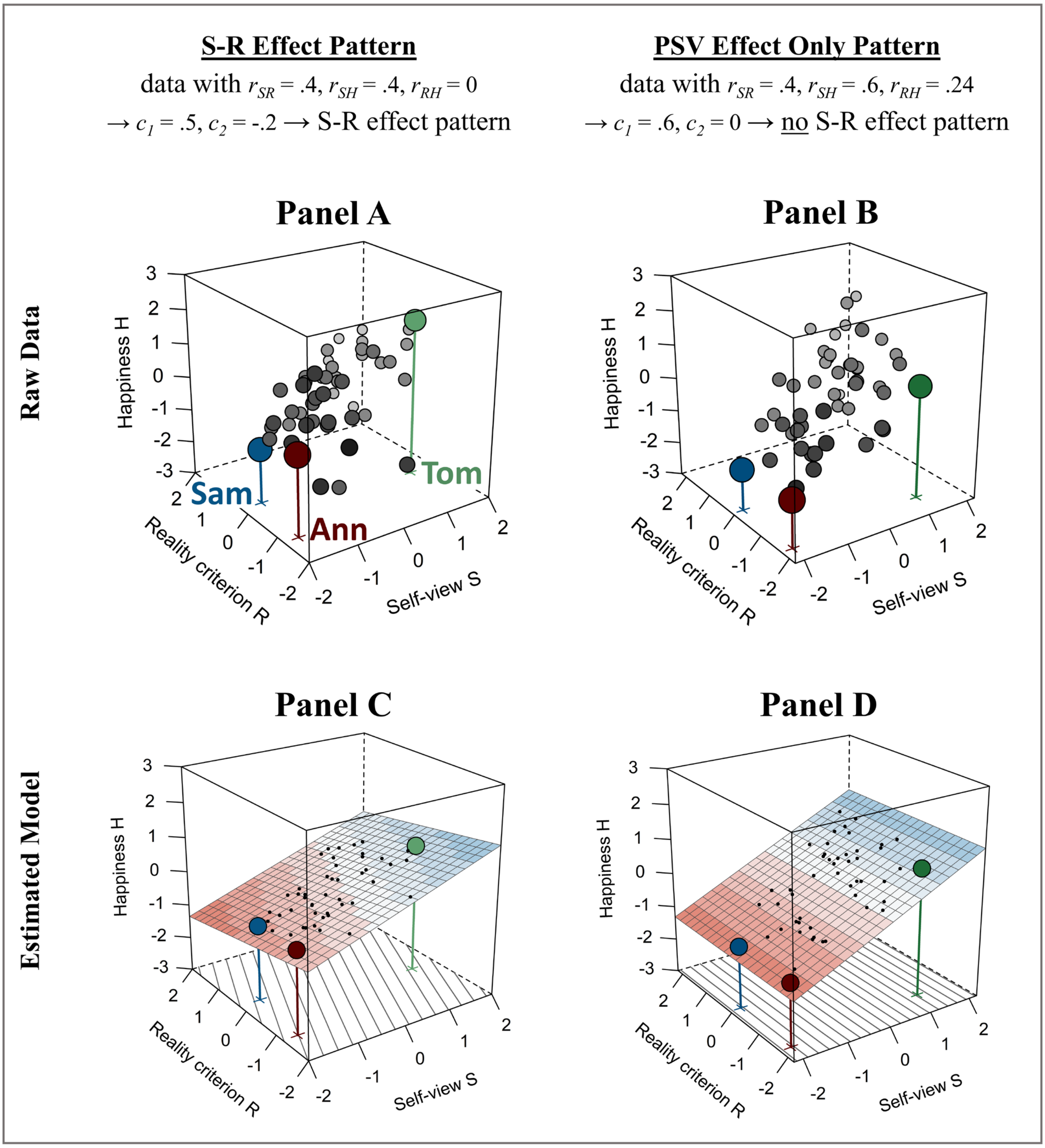
Hence, basic mathematical facts of multiple regression imply that the CRA conditions (c_1>0, c_2<0) exactly represent an expected S-R effect pattern. In particular, this logic ensures that CRA indicates an S-R effect pattern if *and only if* S-R is systematically related to H (irrespective of any main effects of S and R, which are also allowed for). It thereby solves the major limitation of the traditional approach, which relies on the correlation between the difference scores S-R and H ($r_{(S-R)H}$) and has frequently indicated an S-R effect pattern when the outcome was in fact only systematically related to the positivity of people's self-views but not to the discrepancy S-R (Humberg et al., 2018) – that is, when the data show a "*PSV effect only pattern*".[3] CRA avoids this mistake. For example, the data in Figure 1B contradict an S-R effect pattern because people with different levels of SE are about equally happy. In contrast to the traditional approach, CRA accurately detects this, as the coefficients (c_1=.6, c_2=0; see Figure 1D) do not satisfy the CRA conditions.

In sum, the logic behind CRA ensures that when the CRA conditions are satisfied, one can conclude that "people with higher S-R tend to have higher H" in the data at hand. Beyond the conceptual proof just described (see also Humberg et al., 2018), this fact can also be backed up mathematically (Supplement B at osf.io/4p88b) and visually (Supplement H at osf.io/4p88b).

[3] We use the term PSV in its original sense (the psychological construct "positivity of self-view"; Humberg et al., 2018), which conflicts with Fiedler's definition as a pattern of correlations ("PSV (r_{SH}>0; [r_{RH}]=0," p. 793). Moreover, the PSV effect only pattern described here and in Humberg et al. (2018) does not match the "PSV pattern" that Fiedler defines as a pattern of correlations ("PSV pattern (r_{SH}>0; [r_{RH}]=0; [r_{SR}]>0)", p. 793); Fiedler's "PSV pattern" is a "PPZ-correlation-structure" in the notation introduced below.

Figure 1

Example Data and Corresponding Graphs of the Fitted Regression Models (Equation 1)



Note.

For each data set, we drew N = 100,000 cases to ensure that the sample correlations matched the correlations that were specified for the population. The plots with raw data show a random selection of 50 cases. The R code that can be used to generate the data and reproduce all plots and results is provided at osf.io/fbshg. The estimated models are: Panel C: H = 0.5S – 0.2R; Panel D: H = 0.6S + 0R.

Fiedler's Critique of CRA

Fiedler's comment focuses on data with a correlational structure that implies a suppressor effect, namely r_{SR}>0, r_{SH}>0, and r_{RH}=0. We will refer to this structure as a "*PPZ-correlation-structure*" (PPZ = Positive r_{SR} – Positive r_{SH} – Zero r_{RH}). Fiedler observes that CRA indicates an S-R effect pattern for data with a PPZ-correlation-structure because the correlations imply c_1>0 and c_2<0 (see osf.io/fbshg for the mathematical proof and open code that reproduces Fiedler's simulation). The co-occurrence of a zero correlation r_{RH}=0 and a negative regression weight of R (c_2<0) is commonly labeled a "suppressor effect."

Fiedler concludes that his observation "necessarily falsifies the CRA" (p. 793) because "the regression pattern that CRA presumes to rule out a positive self-view account indeed follows necessarily from a suppressor effect entailed in a positive self-view account" (Abstract). That is, Fiedler claims that a PPZ-correlation-structure implies a PSV effect only pattern and thereby contradicts an S-R effect pattern. Researcher X's data (Figure 1A) is a counter example that proves this argument and thereby Fiedler's conclusion about CRA invalid. The data *does* have a PPZ-correlation-structure (r_{SR}=.4, r_{SH}=.4, r_{RH}=0) and thereby satisfies the premise of the argument. However, as explained above, it shows an S-R effect pattern and *not* a PSV effect only pattern, thereby violating the assumed implication. Researcher X's conclusion that "people with higher S-R tend to have higher H" is correct.

More generally, all data with a PPZ-correlation-structure show an S-R effect pattern that is accurately detected with CRA. For an empirical demonstration of this fact, readers can use the R code at osf.io/fbshg to inspect (infinitely many) examples with arbitrary PPZ-correlation-structures (see ComF_SOM.pdf for guidance). More importantly, it is a general principle that follows from two basic mathematical facts: First, all data with a PPZ-correlation-structure (r_{SR}>0, r_{SH}>0, r_{RH}=0) has coefficients c_1>0 and c_2<0 (see osf.io/fbshg for the proof). Second, c_1 is the association between S and H conditional on R, and c_2 is the association between R and H conditional on S. As shown above, this second fact implies that the coefficient pattern "c_1>0 and c_2<0" is one-to-one correspondent to an S-R effect pattern: All data with c_1>0 and c_2<0, including but not limited to data with a PPZ-correlation-structure, show an S-R effect pattern and CRA accurately detects this.

This implies that Fiedler's critique of CRA is unjustified. CRA provides valid conclusions about S-R effect patterns, also in data with a suppressor effect.

We learned during the review phase for this paper that many readers seek further explanation at this point, because they extracted (implicit) arguments from Fiedler's comment that seem yet unaddressed. We will now provide clarifications about suppressor effects and about CRA that clear up these remaining uncertainties.

Clarifications About Suppressor Effects

To many researchers, suppressor effects seem problematic per se. This "bad guy" heuristic presumably stems from the verbal imagery in the psychological literature that often portrays a suppressor effect as an active creature that is messing around in the data, "suppressing" or "absorbing" parts of the variables' variances. The heuristic is often coupled with the idea that correlations and regression weights can be compared in terms of how "true" they are or that one of them could causally "produce" the other and thereby render it spurious or alter its meaning.

However, the "bad guy" heuristic and the involved ideas are not supported by the statistical literature. Instead, methodologists emphasized that, to make a reasoned claim that the suppressor effect is problematic in a given situation, one must rationally explain *why* this attribute of the data affects the conclusion (e.g., Cohen et al., 2002). For the case of CRA, such an argument would need to explain why the zero correlation $r_{RH} = 0$ in combination with $c_2 < 0$ affects the meaning of the regression weights or why it contradicts an S-R effect pattern. Interestingly, Fiedler's comment does not provide such an argument. And in fact, such an argument *cannot exist* because it would contradict basic mathematical principles. Correlations *and* regression weights are descriptions of empirical data. Both of them are equally "true" information about the data and none of them can causally "produce" the other. Neither the suppressor effect ("r_{RH}=0 and c_2<0") nor the observation that r_{RH}=0 can influence the math of regression analysis, the trustworthiness of c_2, or its interpretation as the association between R and H conditional on S, and (together with a respective fact about c_1) this is sufficient for the CRA logic to work.

It also makes sense *conceptually* that suppressor effects play no role for the detection of S-R effect patterns. Fiedler's argument bases on the assumption that bivariate correlations (e.g., r_{RH}=0 in a PPZ-correlation-structure) can inform about the presence or absence of an S-R effect pattern. By definition, however, research on the consequences of SE aims to reveal how different constellations of two variables (the directed discrepancy between S and R) are related to a third one (happiness): The aim is to understand the interrelations between *three* variables at a time. Examining the correlation between *two* of the variables (e.g., r_{RH}) is not decisive for this aim; just like univariate information (e.g., mean(X)=5) is not informative to understand bivariate associations (see osf.io/fbshg for an empirical illustration of this fact). Instead, a multivariate approach is needed, which is offered by CRA.

In sum, the suppressor effect is not a "bad guy," but a descriptive attribute of the data. It plays no role in investigations of S-R effect patterns because it touches neither the logic of CRA, nor the phenomenon of interest.

Clarifications About CRA

During the review process, we also encountered uncertainties about what CRA can be expected to accomplish. In brief, CRA is a statistical method that detects a specific pattern in empirical data. It is applicable when researchers expect that their data show a *linear discrepancy effect pattern* – a linear association between two variables' directed discrepancy X-Y and a third variable Z. In SE research, this is the case when one claims that, for chosen assessments of a self-view variable S, a reality criterion R, and an outcome variable H, people with higher discrepancy scores S-R should tend to have higher values of H. Note that an expected linear association between SE and H translates to this linear discrepancy effect pattern ("S-R related to H") only if SE is operationalized as the algebraic difference S-R. Whereas this is the common choice, the field has yet not reached a consensus on whether S-R or other operationalizations best reflect the *theoretical* construct SE (see Humberg et al., 2018, for an overview). Researchers who prefer a different operationalization (e.g., the residuals in the regression $S = b_0 + b_1R + e$, which implies $SE = e = S - \widehat{b_1}R - \widehat{b_0}$) will not expect a linear discrepancy effect pattern but a different pattern (e.g., "people with higher values of $S - \widehat{b_1}R - \widehat{b_0}$ tend to have higher H"), whose detection requires a respectively adapted version of CRA (see the supplement of Humberg et al., 2018).

Relatedly, a reviewer suggested that maybe Fiedler's conception of an SE effect excludes a suppressor effect by definition. This alternative hypothesis could be tested by combining CRA with tests of the bivariate correlations; but please note that we consider it conceptually implausible to include an assumption about a two-dimensional association (e.g., between R and H) into the definition of a three-dimensional phenomenon (SE effect). In any case, the validity of CRA can be evaluated only by examining whether CRA accurately detects an S-R effect pattern ("S-R related to H") – the empirical pattern it was designed to detect.

Above, we explained that and why this is the case: CRA yields valid conclusions about the presence of an S-R effect pattern. CRA thereby provides a crucial advantage over the correlational approaches (i.e., testing the correlation between S-R and H) that were used to this aim in the past and that often indicated an S-R effect pattern when the data in fact contradicted it. Given that the correct classification of empirical patterns is an integral element of every empirical study, we are convinced that CRA will prove its value for empirical research on the consequences of SE.

At the same time, CRA, like every statistical method, does *not* inform about the causal psychological processes that generated a detected S-R effect pattern. The field of SE research is in full swing to develop theoretical accounts about the behavioral expression and social perception processes underlying the consequences of SE (see Humberg et al., 2019, for an overview), and these developments will certainly continue for several years to come.

Final Remarks

If we may phrase a prediction about which kinds of contributions will most rapidly move the field forward in the next years, it will be establishments and refinements of (a) a consensus about the theoretical construct SE and the terminology used to describe it, (b) process-focused theoretical accounts on the psychological consequences, and (c) empirical methods that put the theories' predictions to an unbiased critical test. We are looking forward to these conceptual, theoretical, and empirical enrichments – and, of course, to observing CRA serve its purpose whenever a discrepancy hypothesis enters the stage.

References

Cohen, J., Cohen, P., West, S.G., & Aiken, L.S. (2002). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (3rd ed.). Routledge. https://doi.org/10.4324/9780203774441

Fiedler, K. (2021). Suppressor effects in self-enhancement research: A critical comment on condition-based regression analysis. *Journal of Personality and Social Psychology, 121*(4), 792–795. https://doi.org/10.1037/pspa0000273

Humberg, S., Dufner, M., Schönbrodt, F.D., Geukes, K., Hutteman, R., Küfner, A.C.P., van Zalk, M.H.W., Denissen, J.J.A., Nestler, S., & Back, M.D. (2019). Is accurate, positive, or inflated self-perception most advantageous for psychological adjustment? A competitive test of key hypotheses. *Journal of Personality and Social Psychology, 116*(5), 835–859. https://doi.org/10.1037/pspp0000204

Humberg, S., Dufner, M., Schönbrodt, F.D., Geukes, K., Hutteman, R., van Zalk, M.H.W., Denissen, J.J.A., Nestler, S., & Back, M.D. (2018). Enhanced versus simply positive: A new condition-based regression analysis to disentangle effects of self-enhancement from effects of positivity of self-view. *Journal of Personality and Social Psychology, 114*(2), 303-322. http://doi.org/10.1037/pspp0000134