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Reply

First things (should) come first: A reply to Gretz & Malshe's "rejoinder to 'endogeneity bias in marketing research: Problem, causes and remedies'"

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Gretz and Malshe (henceforth G&M) in their rejoinder to our article, 'Endogeneity bias in marketing research: Problem, causes and remedies' by Zaefarian, Kadile, Henneberg, and Leischnig (2017) (henceforth ZKH&L) published in *Industrial Marketing Management* discuss different aspects in our argument and note that "[t] here are a few significant errors …" (p. 1). We believe that G&M's rejoinder adds to the discussion of the important problem of endogeneity by complementing our argument and underlining the need to effectively address this issue. While the rejoinder provides the opportunity to further contribute to the discourse on endogeneity, G&M's interpretation and positioning of parts of our paper require some commentary.

The original intention in publishing ZKH&L was to raise awareness about endogeneity and its implications for marketing research. Endogeneity is more of a dilemma rather than a problem—and dilemmata "do not call for solutions, they call for choices" (Ketokivi & McIntosh, 2017, p. 2). Consequently, the focus was on sensitizing the marketing community in general, and industrial marketing researchers in particular about the issue, its causes and potential ways to examine it. G&M refer to two main points as well as additional minor points in ZKH&L. First, G&M argue that we incorrectly describe the 2-stage least squares (2SLS) estimation procedure. Secondly, G&M mention an incorrectly discussed 3-stage least squares (3SLS), both in terms of implementation procedure and appropriate setting. Thirdly, G&M refer to three more specific points that relate to different areas of our article. In the following, we will reply to each of these points.

2-stage least squares (2SLS) procedure. G&M position the approach described in ZKH&L as an alternative methodology to correct for endogeneity bias. In addition, they point out that instead of a residual value from the first stage regression, the 2SLS methodology uses the predictions of the endogenous covariates from the first-stage in the second-stage estimation. We believe there is a misunderstanding which relates to a conflation of 'testing for' versus 'correcting for' endogeneity. We agree with G&M that "the basic idea of the first-stage estimation is to separate the endogenous variable into the likely exogenous part, the predicted values, and the likely endogenous part, the residuals" (p. 10). Yet, either part can be used in the second-stage estimation—but for different purposes. While use of the endogenous part of the offending variable can provide insights into the presence of endogeneity problems, the use of the exogenous part of the offending variable seeks to correct for endogeneity bias. Thus, the procedures described in ZKH&L and G&M have different foci. The procedure described in ZKH&L helps test for, i.e. detect the presence of endogeneity issues and can be conceived as a variation of the Hausman test, while the approach described in G&M (and elsewhere) corrects for endogeneity. Indeed, both approaches complement each other. We acknowledge that we could have been clearer in this regard in our original article.

3-stage least squares (3SLS) procedure. With regard to the 3SLS approach explained in our original paper, it appears that G&M do not differentiate between an instrumental variable-based and a residual-based 3SLS approach. As outlined in Park and Gupta (2012, p. 567), finding a strong and valid instrument is a "critical practical problem".[1] Thus, an alternative approach to cope with this issue has been suggested, which involves the use of the residual-based 3SLS approach. In the absence of an appropriate instrumental variable, the residual-based 3SLS approach uses all or a set of existing exogenous variables in the model (e.g. any independent, moderator and/or control variables) as a combined proxy instrumental variable to separate the likely endogenous part of the offending variable from the likely exogenous part (Cuypers, Cuypers, & Martin, 2017). The basic idea of this approach is that in situations where the relationship between a set of exogenous variables in the model and the offending endogenous variable is spurious, proper model specification should include this set of exogenous

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[1] In general, strict limitations on the validity of instrumental variables have made them extremely difficult to find (Lu, Ding, Peng, & Chuang, 2018; Morck & Yeung, 2011; Park & Gupta, 2012; Rossi, 2014). Weak or "invalid instruments can cause the estimates to differ even when there is no endogeneity bias" (Rossi, 2014. p 671). The severity of the weak instrument problem has led the literature to reach the conclusion that the "cure" based on weak instrument is worse than the "disease" (Rossi, 2014; Semadeni et al., 2014). In this vein, Lu et al. (2018) recommend that in situations where a suspected endogenous variable is approximately exogenous, OLS regression is more efficient than instrumental variable-based approach in correcting for endogeneity.

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variables as antecedents of the offending endogenous variable (Poppo, Zhou, & Li, 2016). Thus, the first stage of the 3SLS approach is to regress any offending endogenous variable against identified exogenous variables in the model to obtain residuals that are free of influence from these exogenous variables. The second stage is to replace the offended endogenous variable(s) with the obtained residual(s). Stage 3 is to add any interaction terms between the residuals of the explanatory variable (s) (i.e. the purified part of the offending endogenous variable) and the moderators. This residual-based 3SLS approach has received strong interest in recent work (e.g. Li, Poppo, & Zhou, 2010; Luo, Rindfleisch, & Tse, 2007; Menguc, Auh, & Yannopoulos, 2014; Poppo et al., 2016; Zhou & Li, 2012).

One important additional benefit of the 3SLS approach (also compared to IV regression) is that it avoids the difficult selection of instrumental variables; identification alone is sufficient (Greene, 2012). Instead of a potentially problematic instrumental variable, the 3SLS technique uses all exogenous variables in the model to create a combined variable that acts as the "best instrument" (Kennedy, 2006)." (p. 617).

Additional points. Besides these two points, G&M mention three additional aspects in our article. One criticizes the limited description of the generalized method of moments (GMM) estimation, the second one refers to Hansen's J-statistic, and the third one indicates disagreement with a statement about the significance of estimates. We acknowledge that our overview article has to manage the thin line between comprehensiveness on the one hand and detail on the other hand. We therefore thank G&M for the additional insights that complement our writing. Regarding the second point, we did not present Hansen's J-statistic (Hansen, 1982) as a direct test of instrument orthogonality to the econometric error term. Rather, we pointed to several tests that help assess exogeneity of instrumental variables. We agree that theoretical arguments are crucial for selecting instrumental variables and that logical reasoning should be presented as well. Moreover, we referred the reader to a review by Bascle (2008), in which Hansen's J-statistic test is explained in detail. Finally, and with regard to the third point, we agree that literature can be subjectively interpreted. However, our statement was made with reference to the results of a simulation study (Semadeni, Withers, & Certo, 2014) and is not based on "a cursory look at recent issues of *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *Management Science*".

Overall, it is pleasing to see that other researchers (including but not limited to G&M) are interested in the topic of endogeneity bias in marketing research and contribute to a deeper understanding of this dilemma. While our original article has focused on introducing endogeneity, its causes and ways of assessment, G&M add to this discussion in *IMM* by providing complementary insights and remarks that may provide impetus for future articles on the topic.

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