Endogeneity bias in marketing research: Problem, causes and remedies

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ABSTRACT

Endogeneity bias represents a critical issue for the analysis of cause and effect relationships. Although the existence of endogeneity can produce severely biased results, it has hitherto received only limited attention from researchers in marketing and related disciplines. Thus, this article aims to sensitize researchers intending to publish in the *Industrial Marketing Management* (IMM) journal to the topic of endogeneity. It outlines the problem of endogeneity bias, and provides an overview of potential sources, i.e. omission of variables, errors-in-variables, and simultaneous causality. Furthermore, the article shows ways to deal with endogeneity, including techniques based on instrumental variables as well as instrument-free approaches. Our methodological contribution relates to providing researchers aiming to publish in IMM with an initial overview of the causes of and remedies for endogeneity bias, which should be considered in designing research projects as well as when analysing data to obtain insights into cause and effect relationships (causal models).

1. Introduction

An increasing number of articles in marketing as well as in related fields such as international business, supply chain management, and operations management have recently pointed to issues associated with endogeneity (Guide & Ketokivi, 2015; Jean, Deng, Kim, & Yuan, 2016; Shugan, 2004). Endogeneity constitutes a critical problem for research as it compromises key conditions for claiming causality (Antonakis, Bendahan, Jacquart, & Lalive, 2010, 2014) and both the direction and the size of its bias are difficult to predict in advance (Hamilton & Nickerson, 2003). A failure to consider and correct for endogeneity in research practice can lead to biased and inaccurate results, and poses the risk of drawing incorrect conclusions about cause and effect relationships between concepts of interest. Even though the issue is much more predominant in naturally occurring data (e.g. regularly and automatically collected customer data at the point of purchase or via web browsing) as opposed to market research data (e.g. data collected through survey questionnaires), and is less of a problem for experimental data (e.g. Anderson & Simester, 2004), any study involving questionnaire or survey design is potentially subject to endogeneity bias (Toubia, Simester, Hauser, & Dahan, 2003).

Endogeneity is most commonly described in the context of ordinary least squares (OLS) estimation, and refers to a situation in which an independent (explanatory) variable correlates with the structural error term (also referred to as 'disturbance term' or 'residual') in a model (Kennedy, 2008; Wooldridge, 2002). In such a situation, the error term is not random and the estimation is inconsistent, which implies that the coefficient estimate of the independent variable fails to converge to the true value of the coefficient in the population as sample size increases. When an independent variable correlates with the error term, the coefficient estimate includes the effect of the respective independent variable on the dependent variable *as well as* the effects of all unobserved factors that correlate with the independent variable and explain the dependent variable, thus rendering its interpretation problematic, or even useless (Antonakis et al., 2010, 2014). If this correlation is ignored, the estimated effect of the observed variable is likely to be biased. This bias is referred to as the *endogeneity bias* (Chintagunta, Erdem, Rossi, & Wedel, 2006).

Endogeneity is a major concern in many areas of marketing and related research, which rely on employing regression-based analyses with the aim to draw causal inferences (Jean et al., 2016). In essence, endogeneity may affect the causal inferences that researchers make with regard to the hypothesized associations between variables, and failure to account for this may lead to spurious findings resulting in misleading theoretical as well as managerial implications (Semadeni, Withers, & Certo, 2014). Against this background, editors and reviewers of various disciplines in the area of management studies increasingly point to endogeneity as a likely alternative explanation for results

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provided in manuscripts they process, and therefore endogeneity considerations become more and more of a (contributing) reason for manuscript rejection (e.g. Guide & Ketokivi, 2015; Larcker & Rusticus, 2010; Shugan, 2004). In spite of the fact that several approaches to address endogeneity have been available for almost three decades, only fairly recently have some of these remedies been applied in studies published in marketing journals (Hamilton & Nickerson, 2003), and the number of researchers proactively correcting for endogeneity still remains very low.

The *Industrial Marketing Management* (IMM) journal has made significant theoretical and empirical contributions to the field of industrial and B2B marketing, as well as supply chain management research. In many respects, the articles published in IMM are rigorous in terms of method, e.g. by assessing several sources of bias such as non-response and common method variance, and by incorporating measurement validity and reliability analyses. However, the issue of endogeneity arguably is a blind spot that has not been sufficiently addressed in research published in IMM to date. So far we have only found a dozen or so papers published in IMM that tackle the issue of endogeneity in their empirical analyses, with the first study being published by Streukens, Hoesel, and de Ruyter (2011). We therefore believe that it is timely for the IMM research community to take the issue of endogeneity seriously. Hence the objective of our paper is to *sensitize researchers and introduce an outline for diagnosing and correcting for potential endogeneity bias in marketing research.* We discuss potential sources of endogeneity and provide a brief overview of techniques available to account for it, followed by an assessment of their robustness. These considerations ought to provide suggestions for researchers in the field of marketing and supply chain management, and especially for future publications in IMM that examine cause and effect relationships.

Our paper thus contributes to the existing knowledge on endogeneity in two ways. First, we clarify the notion of endogeneity and its sources using marketing-related examples. Second, we emphasize the importance of accounting for endogeneity in marketing studies and provide an overview of remedies available to treat endogeneity bias. Overall, we aim at sensitizing researchers who aim at publishing in IMM to the hitherto somewhat neglected topic of endogeneity bias.

2. Sources of endogeneity

Literature emphasizes three primary instances where the condition of exogeneity becomes violated and therefore endogeneity occurs: omission of variables, errors-in-variables, and simultaneous causality (Wooldridge, 2002). The following subsections briefly outline the problems associated with each of these sources of endogeneity.

2.1. Omission of variables

Endogeneity may occur due to the omission of variables in a model. Omission of variables is usually attributable to data unavailability and can result in a violation of the exogeneity assumption if the omitted variable that is associated with the dependent variable is also correlated with any of the independent variables under investigation (Kennedy, 2008; Wooldridge, 2002). In such a situation, the error term will be correlated and the coefficient estimator of the independent variables will be biased. For instance, in investigating the effect of firm resources on foreign market entry modes, other variables that may affect both firms' resource slack and foreign market entry mode include managerial experience and market characteristics. If such variables are omitted from the model and thus not considered in the analysis, the variations caused by them will be captured by the error term in the model, thus producing endogeneity problems.

A common form of omitted-variable-based endogeneity is omitting selection (e.g. Antonakis et al., 2010; Clougherty, Duso, & Muck, 2016; Wooldridge, 2002). This problem arises when respondents self-select

into treatment and non-treatment groups based on unobserved factors that correlate with the dependent and the independent variables under investigation (this is also called the 'choice problem'), which leads to a situation in which the dependent variable is observable for different parts of the sample on a nonrandom basis (Clougherty et al., 2016). Prior work shows that many business phenomena are subject to such self-selection-based endogeneity as they involve organizational choices that are endogenous and self-selected (Hamilton & Nickerson, 2003; Shaver, 1998). For example, firms may select a particular relationship governance mechanism (e.g. formal vs. informal) to achieve a high relationship performance with partner firms based on factors that are unobserved. These factors may, for example, include the level of trust in the partner or the relationship phase. An analysis that tests the effect of relationship governance mechanism on relationship performance will most likely yield biased coefficient estimates unless self-selection is controlled for.

2.2. Errors-in-variables

Besides omission of variables, a further source of endogeneity is errors-in-variables, which refers to problems that arise when variables are imperfectly measured and their true values remain unobserved (Wooldridge, 2002). Measurement errors result from the use of inadequate measurement instruments to capture concepts of interest, or non-comprehensiveness of the data collection method (Kennedy, 2008). Typical examples include scale items being improperly adapted to the research context, wrong aggregation of constructs, failures in survey translation, or non-reliable construct measures. In addition, missing data can be considered as a form of measurement error (Kennedy, 2008). Errors-in-variables constitute an issue when the variables on which data can be collected differ from the variables that influence decisions of relevant actors (Wooldridge, 2002). Measurement error in the dependent variable can cause biases if it is systematically related to one or more of the independent variables under investigation; however, it will play a subordinate role if it is uncorrelated with the independent variables and it is usually of minor relevance as it is captured by the error term of the model. Measurement error in independent variables is considered as important and the properties of the OLS estimation depend on particular assumptions about the measurement error (Wooldridge, 2002). The first assumption is that the measurement error and the observed independent variable are uncorrelated, and that the error term of the model is uncorrelated with the actual (unobserved) and the observed independent variable. In this case, estimation yields consistent coefficients. The second assumption, which is referred to as the 'classical errors-in-variables (CEV) assumption', is that the measurement error is uncorrelated with the actual (unobserved) independent variable, and that the error term of the model is uncorrelated with the actual and the observed independent variable. In this case, the observed independent variable and the measurement error are correlated and the estimation yields inconsistent coefficient estimates: the coefficient estimate will be biased towards zero ('attenuation bias') and the size of this bias depends on the variance of the actual independent variable relative to the variance in the measurement error.

2.3. Simultaneous causality

Endogeneity bias may also be caused by simultaneous causality, which occurs when one (or more) independent variable is jointly determined with the dependent variable, i.e. when independent variables and dependent variables simultaneously cause each other and causal effects run reciprocally (Wooldridge, 2002). Because the error term of the model contains all unobserved factors that influence the dependent variable and, in the presence of simultaneity, the dependent variable influences the independent variable, the error term is also correlated with the independent variable, thus leading to endogeneity

problems. Using the example mentioned above, the link between relationship governance mechanisms and relationship performance may be affected by feedback loops and thus be subject to simultaneity: firms' relationship governance mechanism may influence relationship performance, but relationship performance may also affect the choice of firms' relationship governance mechanism and the decision to adapt it.

A related issue concerns simultaneity in the analysis of panel data and has been referred to as dynamic endogeneity (Abdallah, Goergen, & O'Sullivan, 2015). Past realizations of the dependent variable can influence current realizations of one or more of the independent variables, thus producing endogeneity issues. For example, the current composition of a sales team in an organization is likely to be influenced at least to some extent by its past sales performance. Sales people who failed to achieve sales targets in the past may no longer be part of the current team and may be replaced by new employees who are expected to perform better. Consequently, past performance of the sales team or of sales employees (i.e. past realizations of the dependent variable) has an impact on the current sales team composition. Thus, studying the performance effect of sales team composition creates the risk of drawing the wrong conclusions if the analysis does not consider dynamic endogeneity effects.

As the preceding discussion reveals, sources of endogeneity are manifold and have several dimensions. It is therefore important to note that sources of endogeneity can cumulate and that violation of the condition of exogeneity can have multiple reasons (Bascle, 2008). Fortunately, prior work, especially in the econometrics literature, reveals a broad set of techniques that enable researchers to address endogeneity problems. However, these remedies are often not used, and recent editorials, e.g. in the *Journal of International Business Studies* by Reeb, Sakakibara, and Mahmood (2012), or in the *Journal of Operations Management* by Guide and Ketokivi (2015), as well as a study by Jean et al. (2016) reveal that many researchers are either unaware of the matter of endogeneity, or do not know how to correct for it. The next section will therefore outline different techniques to address endogeneity issues.

3. Addressing endogeneity

Prior work emphasizes that even low levels of endogeneity can produce severely biased and inconsistent results that increase the likeliness of making incorrect causal inferences (Semadeni et al., 2014). It is therefore essential to not only uncover the sources of endogeneity but also to take appropriate actions to address them. Table 1 gives an overview of techniques to address endogeneity issues, which will be discussed below in greater detail.

3.1. Instrumental variables techniques

One common approach to address endogeneity issues is the use of instrumental variables techniques (e.g. Bascle, 2008; Semadeni et al., 2014). The basic idea behind instrumental variables techniques is to decompose the variations in the endogenous independent variable through the use of instrumental variables by focusing on the variations in the endogenous independent variable that are uncorrelated with the error term in the model and disregarding the variations that bias the estimation. Instrumental variables are variables that are uncorrelated with the structural error term in a model, but which are correlated with the endogenous independent variable, and that themselves do not represent explanatory variables in the structural equation (i.e., the original model) (Murray, 2006). An instrumental variable thus 'moves around' the endogenous independent variable, does not directly affect the dependent variable, but affects it indirectly through the endogenous independent variable (Rossi, 2014).

A major challenge associated with the instrumental variables techniques is to identify valid instrumental variables. Validity of instrumental variables depends on two primary conditions: relevance

and exogeneity (Bartels, 1991; Kennedy, 2008; Murray, 2006). Relevance refers to the degree to which an instrumental variable is sufficiently correlated with the endogenous independent variable — with strong instrumental variables having a high correlation and weak instrumental variables having a low correlation with the endogenous independent variable. To assess the strength of instrumental variables, prior studies recommend inspection of the first-stage F-statistic (of 2SLS estimation, see below) and compare the values obtained against thresholds available in the literature (Stock, Wright, & Yogo, 2002; Stock & Yogo, 2004). Exogeneity is defined as the degree to which an instrumental variable and the error term in the model are uncorrelated (Murray, 2006). To assess orthogonality the Sargan (1958) or the more general Hansen's J-statistic (Hansen, 1982), the Basmann (1960) statistic, and the difference-in-Sargan statistic (Hayashi, 2000) may be examined (e.g., see Bascle, 2008for further details; Murray, 2006).

Instrumental variables techniques may use different estimators. One of the most commonly used instrumental variables estimators is two-stage least squares.

3.1.1. Two-stage least squares (2SLS) estimation

2SLS estimation with instrumental variables occurs in two steps. In the first, the endogenous independent variable is regressed on the chosen instrumental variables and the regression residual is saved. In the second step, the dependent variable is regressed on the residual *in lieu* of the endogenous independent variable (Bascle, 2008; Wooldridge, 2010). An example would be the following: let us presume one is interested in the relationship between "Trust" and "Supplier Performance". In this model "Trust" is the independent variable, which is likely to be affected by omitted variables, e.g. pertaining to complex antecedent influences, and thus endogenous, while "Supplier Performance" is the dependent variable. To address potential endogeneity issues, 2SLS estimation may be used. First, "Trust" is regressed on the chosen instrumental variables, say "Engagement" and "Responsiveness", and the residual is obtained:

$$\text{Trust} = b_0 + b_1(\text{Engagement}) + b_2(\text{Responsiveness}) + e$$
$$\text{Trust}_{residual} = \text{Trust} - \text{Trust}_{predicted}$$

In this example, the chosen instrumental variables are those that have been captured besides the substantive variables in the structural equation, and which are assumed to be strongly correlated with the endogenous independent variable "Trust", uncorrelated with the dependent variable "Supplier Performance", and do not explain the dependent variable. Provided that the instrumental variables fulfill the conditions of relevance and exogeneity, the second step of the 2SLS estimation replaces the endogenous independent variable "Trust" with "Trust$_{residual}$" obtained from step one and then regresses "Supplier Performance" against "Trust$_{residual}$":

$$\text{Supplier Performance} = b_0 + b_1(\text{Trust}_{residual}) + e$$

Whilst correcting for endogeneity using instrumental variables increases the likelihood of reporting coefficient estimates that are near their true values, these reported estimates are rarely statistically significant (Semadeni et al., 2014). This occurs because the most problematic aspect of instrumental variables techniques involves the identification of valid instrumental variables. It is imperative that in most cases one should resort to theoretical considerations to determine whether a variable could serve as a valid instrument. However, at times instrumental variables are selected without sufficient conceptual justification. In practice, it remains quite difficult to identify variables that correlate strongly with the endogenous independent variable but not with the error term in the second stage of the technique, which makes fulfilling the essential criteria for instrument selection difficult. Nonetheless, the 2SLS technique remains one of the most widely used methods to address endogeneity bias (Li & Zahra, 2012; Tang & Wezel, 2015).

Table 1
Approaches to address endogeneity problems.

Technique	Description of technique	Endogeneity source	Exemplary studies
Instrumental Variables: Two-Stage Least Squares (2SLS)	Step 1: Regress the endogenous variable on all chosen instruments, which have previously undergone relevance and exogeneity checks, and obtain the residual for the endogenous variable. Step 2: Replace the endogenous variable with the corresponding residual and regress the dependent variable on it.	All	Li and Zahra (2012); Tang and Wezel (2015).
Instrumental Variables: Three-Stage Least Squares (3SLS)	Similar to 2SLS; a moderator is used as instrument to obtain residuals for the predictor. Step 1: Regress each predictor on all moderators, confirm significant relationship between moderatos and the predictor, and obtain residuals for the predictor. Step 2: Replace each predictor with the corresponding residual and regress dependent variable on obtained residuals. Step 3: Add the interaction terms to the model.	All	Poppo, Zhou, and Li (2016); Zhou and Li (2012)
Instrument-Free Approaches: Higher Moments	Instruments are obtained from the available data by exploiting higher-order moments.	All	Erickson and Whited (2002); Lewbel (1997)
Instrument-Free Approaches: Identification through Heteroscedasticity	Instruments are obtained from the available data by exploiting higher-order moments, but information on heteroscedasticity is required (with the aid of introducing an observed grouping variable which explains heteroscedastic error structure).	All	Hogan and Rigobon (2003); Rigobon (2003)
Instrument Free Approaches: Latent Instrumental Variables	A latent variable model is used to separate the endogenous variable into systematic parts, whereby one part is endogenous (possibly correlated with the error) and the other part is exogenous (uncorrelated with the error), which is later used in the equation of interest.	All	Ebbes, Wedel, Böckenholt, and Steerneman (2005); Zhang, Wedel, and Pieters (2009)
Instrument Free Approaches: Copulas	Modeling of the joint distribution of the endogenous variable and the error term (by using a density estimation method) to maximize the likelihood of the structural equation of interest. This is achieved by copulas, i.e. functions that "couple" multivariate distributions to their one-dimensional marginal distribution functions and capture the correlation between the variable and the error.	All	Datta, Foubert, and Heerde (2015); Zhang, Kumar, and Cosguner (2017)
Generalized Method of Moments	The model is specified as a system of equations, based on different time periods, where the endogenous variable is regressed on the instruments (lagged values) applicable to each equation. Instruments in each equation are different (since in later time periods, additional lagged values of the instruments are available) and not exogenous (are present in the model).	All	Fang, Lee, Palmatier, and Han (2016); Shah, Kumar, and Kim (2014)
Matching Method	Propensity score matching (PSM) partials out selection bias by creating a quasi-control group. Using a set of firm characteristics in a probit regression, this technique pairs every firm in the treatment group with a statistical twin firm from a large set of non-participant firms to form the quasi-control group. These statistical twins can be used for comparison to examine the treatment effects.	Selection bias	Garnefeld, Eggert, Helm, and Tax (2013); Chang, Chung, and Moon (2013)
Heckman Two-Step Procedure	Heckman's two-step approach deals with selection bias. Step 1: Run a probit regression to predict the conditional distribution of the treatments with a set of covariates that capture the relevant attributes. Often all control variables and moderators of the study are used for this purpose. Step 2: Add the resulting inverse Mills ratio (IMR) to the final model.	Selection bias	Thomaz and Swaminathan (2015); Fang, Lee, and Yang (2015)
Lagging Independent Variable	This non-statistical remedy aims to alleviate concerns regarding simultaneity effect. This remedy can be considered in the ex-ante research design stage by introducing a time lag between the measurement of the predictor and criterion variables.	Simultaneity	Tang, Fang, and Wang (2014); Griffith, Hoppner, Lee, and Schoenherr (2017)
Natural Experiments	Natural experiment is a unique way of forming treatment and control group to address the sample selection bias during the ex-ante research design stage. This approach is based on occurrence of a "shock" such as change in regulatory or a crisis that only affects a limited number of firms, hence the researcher can form the treatment group based on affected firms, and treat non-affected firms as a control group.	Selection bias	Bertrand, Duflo, and Mullainathan (2004)
Regression Discontinuity Design	The regression discontinuity design is another unique statistical approach to find an indicating factor through which a researcher can assign an observation in the sample to either the treatment or the control group in examining the treatment effects.	Selection bias	Lee and Lemieuxa (2010); Hartmann, Nair, and Narayanan (2011)

3.1.2. Three-stage least squares (3SLS) estimation

3SLS is another instrumental variables estimator for structural equations in which at least one equation contains endogenous independent variables. 3SLS estimation is similar to the 2SLS estimation, with the difference being that moderator variables are used as instrumental variables to obtain residuals for the endogenous independent variable. Hence this technique involves an additional third stage of regression. For example, suppose one is interested in examining the moderating effect of "Behavioral Uncertainty" on the effect of "Trust" on "Supplier Performance". In this model, "Trust" is likely to be endogenous and directly affected by the moderator "Behavioral Uncertainty". 3SLS estimation can be used to correct for this potential endogeneity. In the first stage, "Trust" is regressed against "Behavioral Uncertainty" to assess the relationship between the two variables and obtain residuals for "Trust" that exclude the effect of "Behavioral Uncertainty". These are specified in the following equations:

$$\text{Trust} = b_0 + b_1(\text{Behavioral Uncertainty}) + e$$
$$\text{Trust}_{residual} = \text{Trust} - \text{Trust}_{predicted}$$

In the second stage, "Supplier Performance" is regressed against

"Trust$_{residual}$". In the third stage, an interaction term is entered into the model:

$$\text{Supplier Performance} = b_0 + b_1(\text{Trust}_{residual})$$
$$+ c_l(\text{Trust}_{residual} \times \text{Behavioral Uncertainty}) + e$$

Note that to avoid collinearity, we need to mean center the variables before computing the interaction term. This approach is already used in the marketing and strategy literature (Bharadwaj, Tuli, & Bonfrer, 2011; Menguc, Auh, & Yannopoulos, 2014; Poppo et al., 2016).

3.2. Instrument free approaches

The challenges associated with identifying valid instruments have led to alternative approaches for correcting endogeneity, the so-called instrument-free techniques. Ebbes, Wedel, and Böckenholt (2009) provide an extensive review of instrument free approaches used to mitigate the concerns associated with endogeneity bias. Some of them include: the Higher Moments (HM) approach, where instruments are built based on available data in general regressor-error dependencies models, and can be used together with or in the absence of traditional instruments (Erickson & Whited, 2002; Lewbel, 1997); the Identification through Heteroscedasticity (IH) estimator, in which instruments are obtained in a similar manner to HM, but information of heteroscedasticity is required (Hogan & Rigobon, 2003; Rigobon, 2003); and the Latent Instrumental Variables (LIV) method, whereby the variations in the endogenous independent variable are separated into exogenous (approximated by a latent discrete variable) and endogenous parts (Ebbes et al., 2005). In addition, some researchers recommend joint estimation with copulas - another instrument free method to tackle endogeneity. A copula is a function that 'couples' multivariate distributions to their one-dimensional marginal distribution function and captures the correlation between the independent variable and the error term. Once this correlation is properly handled, the model is unlikely to be affected by endogeneity problems, and estimates for model parameters can be obtained (Park & Gupta, 2012).

Among instrument free approaches, many scholars prefer the application of the LIV method (Ebbes et al., 2005; Zhang et al., 2009), since it uses a latent variable model to account for regressor-error dependencies, and addresses the issues of instrument availability, weakness, and validity. The LIV estimator belongs to the family of thrifty instruments estimators that do not require observed instruments (Ebbes et al., 2005; Ebbes et al., 2009). Furthermore, a clear advantage of the LIV estimator is that it is a likelihood-based approach unlike the HM and IH approaches, which belong to the family of method-of-moments estimators. In the LIV solution, a latent variable model is used to separate the endogenous covariate into systematic parts, whereby one part is uncorrelated with the error term and the other part is possibly correlated with the error term. This permits achieving an unbiased estimate of the effect of an endogenous covariate on the dependent variable. This approach was originally developed in a linear regression setting (Rutz, Bucklin, & Sonnier, 2012) and is also used by marketing researchers when addressing potential endogeneity bias (Zhang et al., 2009).

3.3. Matching method

This method specifically focuses on non-random sampling issues between the treatment and the control group. The idea is that comparison of behavioral data from firms in the sample that did or did not exhibit certain expected outcomes are affected by selection bias. More specifically, given the nature of business marketing research, it is nearly impossible to identify two *identical* firms and allocate them into treatment and control groups, respectively, based on the given desired outcome. For example, to study the relationship among collaborative networks, absorptive capacity, and new product development (NPD), it

is virtually impossible to find collaborative networks and absorptive capacity of two identical firms, one with high NPD performance, and one that does not practice NPD. The non-random sampling issue explained in this example is addressed through creating a quasi-random sample.

This technique was originally developed for binary treatments (Rosenbaum & Rubin, 1983), however, it has been extended to treatments with more than two categories (Hirano & Imbens, 2004). Using probit regressions, the matching method pairs every treatment firm with a firm from the control group to create a quasi-control group and randomizes the data effectively. To build this quasi-control group, a relatively large secondary dataset of control firms is needed. For example, Chang et al. (2013) used some 149,000 control firms to successfully find 1811 matched pairs of firms (statistical twins) out of their 2195 treatment groups. There are different techniques for matching statistical twins (Smith, 1997). The matching method helps researchers to compare and contrast two statistically twinned firms to examine the treatment effect. The propensity score matching (PSM) technique has been widely used in recent studies (e.g. Chang et al., 2013; Garnefeld et al., 2013; Schilke & Lumineau, 2016).

3.4. Heckman two-step procedure

Heckman's (1979) two-step procedure addresses endogeneity bias that exists in self-selected samples. Consider the relationship between "Trust" and "Supplier Performance" as mentioned above. It is very likely that "Trust" in a relationship with a supplier is a choice or decision variable, i.e. managers of the buyer firm 'choose' to have certain levels of trust in their relationship with a given supplier. This means that the level of "Trust" in our sample is non-random and as such it is subject to random selection bias, which causes endogeneity. To address this endogeneity bias, Heckman (1979) developed a two-step procedure that corrects for this bias. In the first step of this approach, a probit regression is run to model the conditional distribution of the treatment with a set of covariates that captures the relevant attributes. The relevance of the chosen set of covariates needs to be theoretically justified. To predict the propensity scores, some recent studies used all control variables as well as the moderators in their model (e.g. Schilke & Lumineau, 2016). This procedure needs to be repeated for each treatment (i.e. independent variable) of the model. In a second step, the self-selection bias is corrected by including the resulting inverse Mills ratios (IMR) into the final regression models before testing hypotheses. Alternatively, to assess whether endogeneity biases the results, the main dependent variable can be regressed on the obtained propensity scores as well as the predictors and the significant pattern[1] can be compared against a rival model wherein the propensity scores are excluded. If the overall pattern of significance remains the same in the two models, it can be safely concluded that endogeneity is not a potential threat to the results.

The Heckman's two-step approach has been commonly used in marketing and management research (Heide, Kumar, & Wathne, 2014; Schilke & Lumineau, 2016; Thomaz & Swaminathan, 2015; Verhoef, 2003). However, this approach, despite being useful and popular among researchers, has some limitations. For example, at least one variable with a non-zero coefficient in the selection equation in step one should not be included in the final equation in step two. This variable essentially plays the role of an instrument, which is often not easy to

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[1] To explain the significant pattern further, note that the main model is the focal conceptual model of the study that typically consists of a set of independent variables and perhaps some interaction terms, which are linked to the main dependent variable. The rival model is the same as the main model, with the addition of the correction term residual variable (as such the rival model has one additional variable). If those independent variables and interactions terms that were significant in the main model remain significant in the rival model, and the additional residual variable is not significant, then one can conclude that endogeneity is not an issue.

find or justify, specifically in business marketing research. Furthermore, given that this approach aims to address selection bias, the first step of Heckman's technique formulates a probit model to predict the probability of selection, hence the 'choice' variable, i.e. the predictor needs to be a dummy variable that takes the value of 1 if the treatment is selected, and 0 otherwise. To overcome this limitation, one solution is to recode the predictor variable into a dummy one (e.g. Schilke & Lumineau, 2016). Alternatively, Garen (1984) provides another two-step approach for selectivity-bias correction with a continuous choice variable (e.g. Robson, Katsikeas, & Bello, 2008).

In the example of trust and supplier performance used above, one would need to regress trust against a set of factors (such as firm and industry characteristics) that affect trust. The output from this regression model may predict that a buyer firm with a given set of attributes is more likely to have trust in the relationship with the focal supplier. In practice, researchers often include all the control variables, independent constructs, and moderators except for the main dependent variable (s) into the correction regression model to predict the choice variable. Then, in the second step, they add the predicted errors from this correction regression equation into the second-stage performance equation.

3.5. Lagging independent variable

Endogeneity due to simultaneity or reversed causality can also be tackled by using the *lagged endogenous regressor technique*. A temporal separation through introducing a time lag between the independent and dependent variables can reduce this bias. Given the example of collaborative networks and NPD mentioned above, it is likely that there exists a simultaneity effect between the two. Measuring collaborative networks in year t-1 and NPD in year t (i.e. the dependent variable is measured in a time-lagged fashion) can significantly alleviate the endogeneity concern stemming from simultaneity effects. However, this approach comes with its own limitations. For example, one can argue that the NPD practices in year t-2 can influence the collaborative networks in year t-1, and are correlated with NPD in year t; as such the lagged collaborative networks is still endogenous. This criticism limits the potential benefits and employability of this approach.

3.6. Techniques for panel data

Endogeneity in panel data research takes a different form in comparison to cross-sectional research design based on surveys. A panel is typically comprised of thousands of repeated data observations. This enables researchers to apply complex statistical tests to remedy potential endogeneity bias (Covin, Garrett, Kuratko, & Shepherd, 2015). One such test is the Durbin-Wu-Hausman test, which is essentially the equivalent of the 2SLS approach, which evaluates the consistency of an estimator when compared to an alternative but less efficient estimator that is already known to be consistent. This way it helps researchers to evaluate if a statistical model corresponds to the data.

If endogeneity is likely to occur due to omitted variables in the panel data, then the within-groups estimator could mitigate the existing bias. However, it is important to note that the within-groups estimator will only produce consistent parameters if the independent variables are strongly exogenous, i.e. past realizations of the dependent variable are not correlated with current values of the independent variable (Wintoki, Linck, & Netter, 2012). Therefore, if the condition of exogeneity of the independent variables is violated, within-group estimation is not an adequate technique to correct for endogeneity. On the other hand, if simultaneity is the suspected cause of endogeneity in the panel (i.e. the present observations of the dependent variable affect the present observations of one or more of the independent variables, and vice versa), then the whole OLS and within-groups estimators will be biased. A solution for this situation would be a comparison of the OLS

estimator of the coefficient on the lagged dependent variable with the equivalent within-groups estimator. If both estimators are very different, then endogeneity is likely to be an issue (Abdallah et al., 2015).

Generalized Method of Moments (GMM) encompasses a system of two sets of equations developed by Blundell and Bond (1998). It assumes that the error terms are independently and identically distributed across the data set observations. Notably, GMM is one of the endogeneity bias remedies that corrects for all three types of endogeneity. However, in contrast to 2SLS and 3SLS, it does not rely on external exogenous instruments, which in practice may be difficult to identify (Wintoki et al., 2012), but consists of a system of two sets of equations, each with its own internal instruments (Abdallah et al., 2015). GMM approaches applied in marketing research provide further insights regarding controlling for endogeneity in panel data (e.g. Fang et al., 2016; Shah et al., 2014).

3.7. Other remedies

Other approaches employed by some scholars focus on incorporating additional controls to account for correlation with unobservable factors and increase the robustness of endogeneity controls (Bharadwaj et al., 2011). Specific controls are chosen following the logic that they should be correlated with the dependent variable in order to examine whether their presence in the model is going to influence any of the main effects (e.g. Mizik & Jacobson, 2008).

3.7.1. Natural experiments
An approach to address the effect of self-selection bias is to study the variable of interest before and after a particular intervention has occurred. A change in the regulatory environment, financial crises, sanctions, bans, or natural disasters are among different types of interventions that may affect a firm as an element of shock. Such interventions are considered as a natural or quasi-experiment (Reeb et al., 2012). Seeing the shock as the treatment effect, the occurrence of such interventions allows for comparisons of the behavioral data of the affected focal firm before and after the shock.

A major concern with this approach is that one can argue that once a shock has occurred, many factors may change and so the comparison of, for example, post-crisis against pre-crisis situations is not meaningful. To address this concern, the researcher needs to control for this by including a set of firms that are not affected by the intervention phenomenon as a control group and compare the difference in the affected group to the difference in the non-affected group (Reeb et al., 2012). This approach is often referred to as the difference-in-difference (DD) test and has already been used in marketing research (e.g. Dhar & Baylis, 2011; Rossi & Chintagunta, 2016; Xu, Forman, Kim, & Ittersum, 2014).

3.7.2. Regression discontinuity design
Regression discontinuity (RD) is yet another approach to deal with non-random treatment effects. This approach was first developed by Thistlethwaite and Campbell (1960) to estimate treatment effects. The main idea behind this method is to find a factor that can delineate how an observation becomes part of the treatment group and seeks to exploit the cut-off point for this identified factor (Reeb et al., 2012). The discontinuity in this method refers to identifying the threshold or the cut-off point that can distinguish the treatment from the control group. Early applications of this technique appeared in educational studies. For example, several studies have used this technique to exploit threshold rules used by educational institutions to investigate the effect of financial aid and class size (Angrist & Lavy, 1999), and school district boundaries (Black, 1999). The regression discontinuity design technique enables researchers to compare firms that are just above the cut-off point against those firms that are marginally below the cut-off point (for example of use see Hartmann et al., 2011). Note that comparisons between firms that are just below or just above the cut-off point is

similar to the propensity score model.

4. Conclusions

Research has demonstrated what could happen when no actions are taken to correct for endogeneity (Villas-Boas & Winer, 1999). The outcomes clearly show that not accounting for endogeneity can result in misleading results, incorrect effects and inflated estimate levels in the model in comparison with analyses achieved when endogeneity corrections took place. Thus, if the researcher suspects the presence of endogeneity, the first logical step would be to identify the source of it, in order to proceed with the most suitable treatment. In line with the approaches mentioned in the previous section of this article, it is important for researchers to clearly realize which methods they can and should use to address the specific problem of endogeneity, which they face in their research. While in some cases several techniques might be equally applicable and suitable to implement, the decision concerning endogeneity corrections should be based on several factors, such as research design and data collection instrument, sample size, complexity of the model, and underlying theory and research context.

Additionally to the remedies discussed, researchers are also urged to consider alternative ways of dealing with endogeneity issues. First of all, the research community publishing in IMM ought to endeavor to collect better quality data. This could be achieved via collecting additional relevant data (surveys and experiments) that could help explain hypothesized effects (Liu, Otter, & Allenby, 2007; Swait & Andrews, 2003). Another solution could be to make explicit *ex ante* assumptions about the nature of the endogeneity (i.e. use a strong theory to enhance conceptual arguments) and directly incorporate that relationship into the estimation (e.g. Aaker & Bagozzi, 1979).

Overall, *analysis and correction for endogeneity bias ought to become standard practice for causal modeling in articles published in IMM*, similar to how non-response bias, common method bias, and outer measurement model analyses regarding validity and reliability have become part of the standard quality assurances and reporting templates.

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