Journal of the Academy of Marketing Science (2019) 47:479–498
https://doi.org/10.1007/s11747-019-00630-4

REVIEW PAPER

Endogeneity and marketing strategy research: an overview

Oliver J. Rutz[1] **· George F. Watson IV**[2]

Received: 26 March 2018 / Accepted: 10 January 2019 / Published online: 23 February 2019

Abstract
Endogeneity in empirical marketing research is an increasingly discussed topic in academic research. Mentions of endogeneity and related procedures to correct for it have risen 5x across the field's top journals in the past 20 years, but represent an overall small portion of extant research. Yet there is often substantial difficulty in reconciling issues of endogeneity with many of the substantive questions of interest to marketing strategy for both theoretical and/or practical reasons. This paper provides an overview of main causes of endogeneity, approaches to addressing it, and guidance to marketing strategy researchers to balance these issues as the field continues to move towards more methodological sophistication, potentially at the expense of managerial tractability.

Keywords Marketing strategy · Endogeneity · Research methods · Review paper

Marketing strategy research has always been driven by a fundamental desire to help marketing managers make better decisions (e.g., Reibstein et al. 2009; Varadarajan 2010). Managerial relevance can be defined as the level to which academic knowledge to can be leveraged by managers to improve his or her job-related thoughts and actions in the pursuit of organizational goals (Jaworski 2011). The focus on managerial relevance and real-world implications could set marketing strategy research apart from the other academic marketing domains (Houston 2016). However, there is an increasing tension between this core trait of managerial relevance and methods focus in a progressively more technical (academic) world. Prominent marketing strategy researchers have argued that a heavy focus on methodological rigor for its own sake can lead to work that is irrelevant and atheoretical (Lehmann et al. 2011), which could hamper influence in managerial circles. Conversely, Houston (2016, p. 561) points out that some marketing strategy researchers "continue to ask interesting questions but have failed to keep up with methodological advances in the field."

Empirical marketing strategy research often relies on past data to understand "what happened" and "why it happened" with the aim to improve marketing strategy going forward, e.g., reallocate marketing dollars. This often informs causal claims about the impact of marketing strategy implementation and prescriptive advice for managers to follow. However, if models that use observational data from the past are potentially biased, e.g., model elasticities do not correctly represent the true effects of a certain marketing action, this raises concerns of the validity of forecasts of the performance of the new and improved marketing strategy. Generally, these concerns are summarized under the label of endogeneity and they relate to potential biases induced from endogenous variables rendering parameters uninterpretable and causal relationships misleading (e.g., Berry 1994; Villas-Boas and Winer 1999; Wooldridge 2010). Mentions of endogeneity and related procedures to correct for it have risen 5x across the field's top four journals (see Fig. 1), and continue to be of concern in many of the field's high quality journals (McAlister 2016). Yet there often can be substantial difficulty in reconciling issues of endogeneity with many of the substantive questions of interest to marketing strategy for both theoretical and/or practical reasons (Houston 2016; McAlister 2016). Endogeneity is a concern for which, we believe, no "perfect" solution exists. Even when a researcher is able to use a field experiments, often

John Hulland served as Editor for this article.

✉ Oliver J. Rutz
orutz@uw.edu

George F. Watson, IV
george.watson@pdx.edu

[1] University of Washington, Michael G. Foster School of Business, 420 PACCAR Hall, Seattle, WA 98195-3226, USA

[2] Portland State University, The School of Business, Karl Miller Center, 550C, Portland, OR 97201-0751, USA

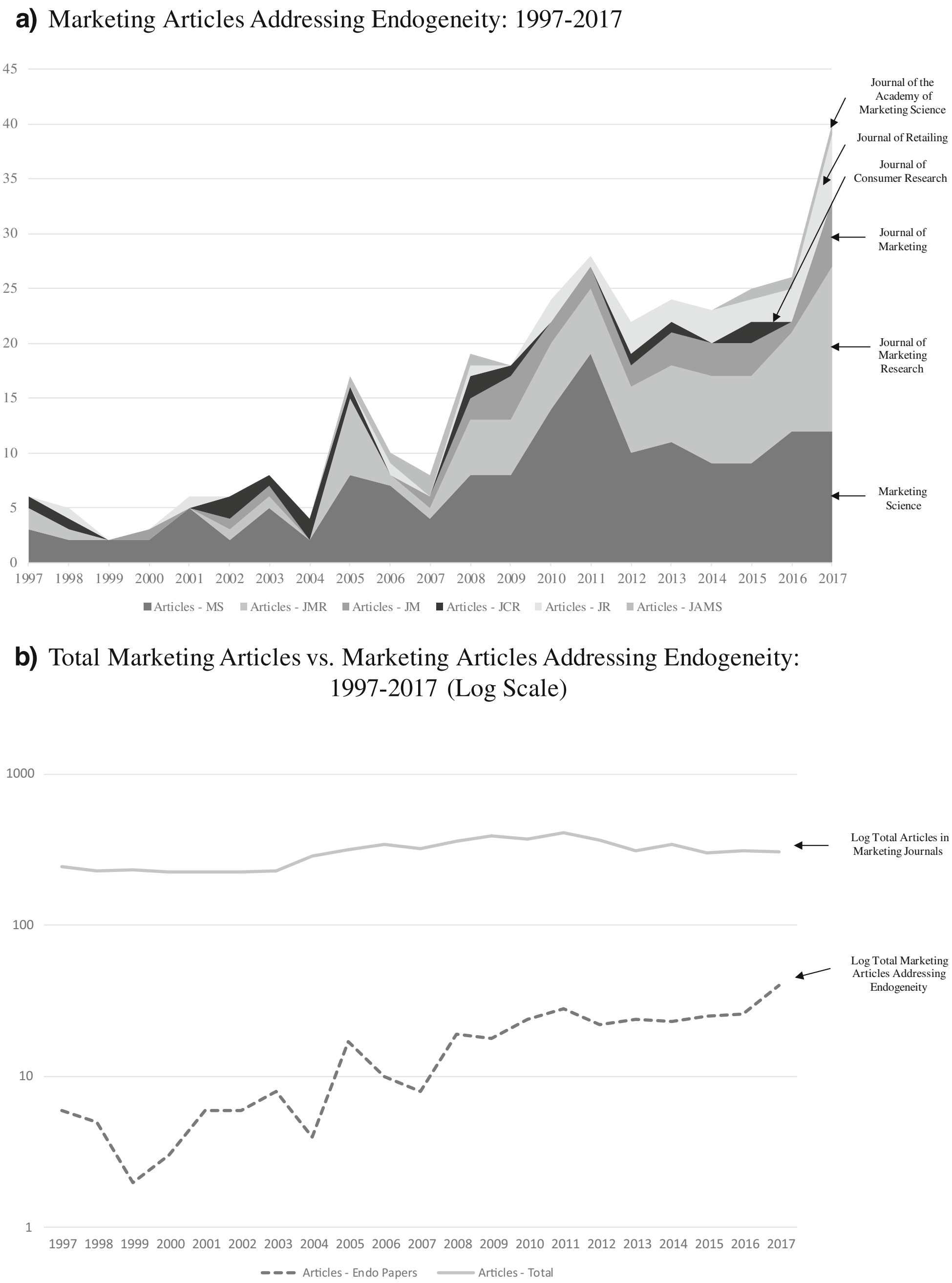

Fig. 1 Panel **a**: Marketing Articles Addressing Endogeneity: 1997–2017. Panel **b**: Total Marketing Articles vs. Marketing Articles Addressing Endogeneity: 1997–2017 (Log Scale). Reuters' Web of Science articles with keywords "endogeneity," or "instrumental variable" or "latent instrumental variable" or "control function" or "structural model" or "field experiment" or "copula," but not "structural equation model"in Marketing Science, Journal of Marketing Research, Journal of Marketing, Journal of Consumer Research, Journal of Retailing, and Journal of the Academy of Marketing Science

considered the gold standard when it comes to causality, endogeneity is still a concern as "clean" experiments are rarely achievable in today's world of lightning-fast competitive response and algorithms (Johnson et al. 2017). In this light we aim to discuss the common sources of potential endogeneity biases and manageable remedies available to address these biases. Through this lens we intend to provide guidance to marketing strategy researchers in terms of balancing these issues by fostering a contemplative research perspective that emphasizes upfront conceptual analysis to address potential endogeneity, rather than an ad hoc application of some statistical "fix" (Rossi 2014).

It is important to note that the endogeneity issue potentially is significantly different and more problematic to address than many other issues that empirical marketing research has grappled with and addressed over time. For example, a main research thrust in the 80s and 90s was to address unobserved consumer heterogeneity, i.e., consumers differ in their underlying and unobserved preferences. Marketing models need to account for these unobserved preference differences to inform valid marketing strategies, e.g., understanding the effects of price promotions on brand loyals (i.e., low price elasticity) and switchers (i.e., high price elasticity). Many papers have focused on the issue of unobserved consumer heterogeneity and two main approaches have emerged – either a segment-based approach or an individual-level approach (e.g., Wedel et al. 1999). While there was much discussion on which approach was preferable, Andrews et al. (2002) showed that both methods work equally well. Unfortunately, as the issue of endogeneity is heavily dependent on the context of the study, it is not clear that a set of "perfect" methods will ever exist, or that one can evaluate the different methods that do exist to consistently compare and rank their performance.

Our paper is aimed at marketing strategy researchers who want to develop an understanding and overview of common, yet addressable, endogeneity issues in empirical work.[1] We follow the framework on review articles laid out by Palmatier et al. (2018) and successfully implemented in such articles as Grewal et al. (2018) on meta-analyses and Sorescu et al. (2017) on event studies. We do not aim to provide an exhaustive econometric textbook-like discussion of endogeneity, nor showcase the latest methods for complex cases of endogeneity. For more in-depth technical treatment of endogeneity, we refer the reader to such articles as Ebbes et al. (2016) or Papies et al. (2017). Rather, we aim to foster a common language and knowledge basis for discussions of endogeneity issues among strategy researchers and in the review process. In addition, we aim to direct interested readers to more in-depth technical literature and illustrative substantive applications related to each topic. As said above, we believe no perfect solution exists for endogeneity at this point in time. We will discuss popular approaches and also point out potential issues related to these approaches. Depending on the data at hand and availability of other supplemental data, different approaches might be a good or bad fit to address potential endogeneity issues. From our perspective understanding endogeneity in empirical research and discussions on how to treat it are important. We believe every empirical researcher should build a good foundation of skills to address endogeneity issues as best as possible, for which we hope our exposition will prove useful.

We begin with a brief discussion of the problems that arise from endogeneity and why endogeneity is an important consideration in empirical marketing strategy research. Second, we provide an overview of the most common sources of endogeneity including omitted variables, simultaneity, and measurement error, as well as a thorough organization of pertinent literature so that strategy researchers may better recognize and address potential issues in their own research. We follow this with an overview of the six main approaches for addressing endogeneity in empirical research, which consists of the instrumental variable (IV), the control function, the latent instrumental variable (LIV), the Gaussian copula, the field experiment, and structural econometric model (vs. reduced form) approach. For each, we discuss major benefits and limitations, its basic methodological specification, corresponding estimation procedures, in addition to appropriate use and related assumptions. Finally, we provide four general guidelines to marketing strategy researchers to help empower a harmonious mix of managerial relevance and methodological sophistication going forward.

Our works aims to contribute on three main dimensions. First, revisiting the endogeneity issue and clearly outlining the different sources of endogeneity should enable authors and reviewers to have a productive discussion on the concerns with a modeling strategy in lieu of simply stating the dreaded "everything is endogenous" and dismissing an otherwise good paper. Careful, a priori thought can mitigate potential endogeneity risks before they arise, as well as selection of appropriate modeling approaches can both serve to preempt reviewer concerns to help researchers focus on the substance of their manuscripts and advance topics of managerial interest.

Second, given the identified concerns, we discuss what potential methods are useful to address them as best as possible. Although not exhaustive, we believe our comprehensive discussion of the major approaches to empirically addressing potential endogeneity in a researcher's model provides a starting point for more in-depth analysis and recognition of potential pitfalls for any research undertaken outside of laboratory settings. Better understanding on these approaches and their application to various contextual settings should serve to strengthen the reliability and validity of a researcher's findings, and potentially save time in the review process.

Third, we want to emphasize that none of the methods to address endogeneity is perfect and they all have certain costs attached – there is no "best" way to address endogeneity, only best practice. We aim to provide a way for strategy research to address endogeneity as best as possible given the existing tools available to balance empirical rigor and managerial tractability. We do not see these two goals as mutually exclusive, but rather as compliments that can advance managerially relevant marketing thought via robust analysis. By employing the most appropriate and up to date methods, we believe that marketing strategy researchers can still provide meaningful substantive findings precisely due to, rather than despite of, robust methodological foundations.

Main sources of endogeneity

Endogeneity is an increasing concern for many areas of marketing, management, and business related academic research that aim to draw causal inferences from statistical analysis of non-experimental data (Lehmann et al. 2011). Broadly speaking, endogeneity concerns arise in situations where an explanatory or "independent" variable correlates with the error term

[1] Our discussion on endogeneity focuses on empirical research with firm data. For researchers interested in endogeneity issues in survey data, Sande and Ghosh (2018) provide an overview.

(residual) of a specified model, rendering estimates inconsistent. This is because the coefficient estimate of the compromised explanatory variable also contains the effect of unaccounted for variable(s) that also partially explain the dependent variable (Chintagunta et al. 2006). Endogeneity bias of this form is particularly problematic when researchers attempt to claim causality with a model where coefficient estimates may be biased or spurious because of misspecification. Most commonly, endogeneity bias will arise from three main sources: omitted explanatory variables, simultaneity, and measurement error (Wooldridge 2010).

Why is this important a reader might wonder? Typically, the goal of empirical work is to determine the effects of independent variables (X) on dependent variables of interest (y). In marketing, we model managerially relevant dependent metrics such as sales or profit driven by (independent) marketing inputs such as advertising and price. The goal of such models is to calibrate the relationship between inputs (independent variables) and outputs (dependent variables). For example, what role does online advertising play in generating sales? More important, the marketing strategy going forward is formulated based on these estimated relationships, for example, advertising spend is decided based on advertising effectiveness or advertising elasticity calculated using the estimated advertising effect. If the measure of advertising effectiveness is biased due to endogeneity, then the resulting strategic advertising spend decision will not be optimal in terms of spending firm resources on marketing. While we are not aware of any work comparing estimates of models without endogeneity control to models with endogeneity control, Papies et al. (2017) provide some initial evidence with regard to the existence of bias in a meta-analysis across studies. They find that for three different marketing variable elasticities–price, advertising and personal selling–studies without endogeneity controls report different effect sizes compared to studies with endogeneity controls.

We will discuss common sources of endogeneity in detail next and show how these biases manifest themselves using stylized models for ease of exposition. Additionally, we illustrate endogeneity within the context of a running example in which a hypothetical researcher has interest in examining the effect of online advertising on sales, a common marketing strategy decision variable and firm performance outcome, respectively. From our perspective, the first step to address endogeneity is to understand the potential source(s) that apply given the research setting, its data, and the modeling approach chosen by the researcher or manager (Table 1).

Omitted variable bias

One of the most common sources of endogeneity is also one of the most difficult to diagnose due to uncertainty pertaining to the omission of explanatory variables. Endogeneity

Table 1 Main sources of endogeneity in marketing strategy research

Source of endogeneity	Definition	True data generating model	Researcher observation	Endogeneity problem	Examples in marketing literature
Omitted variable bias	Exclusion of an explanatory variable that is correlated with both the dependent variable and one or more included explanatory variables.	$y = x\beta + z\gamma + \varepsilon$ ε i.i.d error term	$y = x\beta + \upsilon$ υ i.i.d error term	$\upsilon = z\gamma + \varepsilon$ If $\gamma \neq 0$ and x and z are correlated, then x is correlated with the error term υ, making x endogenous.	Archak et al. (2011); Bronnenberg and Sismeiro (2002); Calantone et al. (1996); Rutz et al. (2012)
Simultaneity	The occurence of two variables that simultaneously affect one another.	$y = x_1\beta_1 + zy + \varepsilon_1$ $z = x_2\delta_2 + y\phi + \varepsilon_2$ ε_1 and ε_2 i.i.d. error term (potentially correlated)	$y = x\beta + z\gamma + \upsilon$ υ i.i.d. error term	$E(z\upsilon)\neq 0$ making z endogenous.	Bagozzi (1980); Ailawadi et al. (2008); Elberse and Eliashberg (2003); Rinallo and Basuroy (2009)
Measurement error	The inclusion of imperfectly measured variables without accounting for their error.	$y = x\beta + \varepsilon$ ε i.i.d error term	$\dot{x} = x + \eta, y = \dot{x}\beta + \upsilon$ υ i.i.d. error term. The researcher observes y and x with measurement error,, and is the measurement error	$\upsilon = \eta\beta + \varepsilon$ both x and υ are a function of η, making x endogenous (e.g. attenuation bias).	Fornell and Larcker (1981); Grewal et al. (2004), (2013); Mallapragada et al. (2015)

violations may result from the omission of a variable that correlates with the dependent variable of interest as well as any of the included explanatory variables (e.g., Wooldridge 2010; Archak et al. 2011). Omitted variable problems may be due to data unavailability or selection bias, wherein the "treated" observations are selected in non-random ways from "non-treated" observations based on an omitted factor that correlates with the included dependent and independent variables (Clougherty et al. 2016). One typical example of omitted variable bias in the marketing context is price endogeneity. Firms do not set prices randomly but set them taking consumer response, competition and seasonality into account. Generally, the researcher does not observe the pricing mechanism the firms employs, introducing omitted variable bias due to the non-randomness of the (observed) price in the dataset. A pressing example of selection bias is targeting in the digital space. Targeting algorithms determine whether an ad is shown to a consumer. If the ad is shown, one can track conversion behavior, for example, clicking on the ad. Thus, one could calculate the advertising effectiveness based on these click data. But as the algorithm that determines whether the ad is shown selects "better" consumers (i.e., targets), the estimate based on these data would be biased upward as the algorithm has deselected consumers who are less likely to click. When the effect of an omitted variable is not taken into account in the model and instead enters into the variation of the error term, coefficient estimates of the included explanatory variables suffer an endogeneity bias.

Generally, omitted variable bias may take the following form. Supposed the true data generating model is

$$y = x\beta + z\gamma + \varepsilon, \tag{1.1}$$

where,

y Firm Performance, e.g., sales,
x Marketing Strategy, e.g., online advertising spend,
z one or more influential variables, e.g., competitor pricing mechanism,
ε i.i.d. error term.

Above, β and γ are the parameters of interest. Yet, the researcher only observes y and x, omitting z, and then estimates

$$y = x\beta + \upsilon, \upsilon \text{ i.i.d.error term.} \tag{1.2}$$

This leads to the problem where

$$\upsilon = z\gamma + \varepsilon. \tag{1.3}$$

If $\gamma \neq 0$ and x and z are correlated, then x is correlated with the error term υ, making x endogenous.

Indeed, many phenomena of interest to the researcher are likely to suffer from potential omitted variable bias as marketing managers respond and adapt their strategy to factors that are unobservable to the researcher. Utilizing common ordinary least squares (OLS) estimation will distort coefficient estimates in the presence of the type of endogeneity described above (e.g., $\text{cov}(\upsilon, \varepsilon) \neq 0$). Compounding this issue is that in many contexts of research, it may be impossible to determine all potential explanatory variables, accurately measure them, and include them in the model. Consequently, the researcher is likely to have difficulty accounting for endogeneity in their model with control variables alone.

Simultaneity

Simultaneity in variables occurs when one or more explanatory variables are caused simultaneously and reciprocally with the specified dependent variable in a model (Bagozzi 1980; Wooldridge 2010). Continuing our example, this would manifest itself as the effect of online advertising on sales and the reciprocal effect of sales on online advertising. Compared to offline advertising that often needs to be set far in advance and could not be changed, online advertising (e.g., banner ads, search engine advertising) can be changed nearly instantaneously in many settings. First, online advertising affects sales as many studies have shown. However, if online advertising leads to higher sales it will lead to higher firm profits assuming that advertising is cost effective. In this case the firm will have higher resources, or will expect higher resources in the future, and might increase its online advertising, leading to a feedback effect and potential simultaneity concerns.

In this scenario, analysis of a dataset containing sales information (y) and corresponding online advertising (x) ignoring simultaneity would result in the error term of the model correlating with the explanatory variable, producing endogeneity problems and biased coefficient estimates. Relatedly, auto-correlation of the dependent variable in past periods with that of the explanatory variable in the current period may also result in endogeneity bias.

More generally, simultaneity takes the following form. Suppose the true data-generating model is

$$\begin{aligned} y &= x_1\beta_1 + z\gamma + \varepsilon_1 \\ z &= x_2\delta_2 + y\phi + \varepsilon_2 \end{aligned}, \tag{2.1}$$

where,

y Firm Performance, e.g., sales,
x_1 and x_2 Marketing Strategy at time $t = 1$ and $t = 2$, e.g., online ad spend,
z one or more influential variables, e.g., competitor pricing mechanism,
ε_1 and ε_2 i.i.d. error term (potentially correlated).

Yet the researcher only observes y, x and z, and then estimates

$$y = x\beta + z\gamma + \upsilon, \ \upsilon \text{ i.i.d.error term.} \tag{2.2}$$

This results in $E(z\upsilon) \neq 0$, making z endogenous.

The main difficulty with this issue is that making causal claims based on simultaneously occurring variables requires disentangling the temporal order in which they influence each other. In the above example, advertising can increase sales, but increased sales provide a greater advertising budget (e.g., Dekimpe and Hanssens 1995). Because in the presence of simultaneous causation, the dependent variable also "causes" the explanatory variable and thus the error term in the equation is correlated with the explanatory variable, violating OLS assumptions and resulting in biased estimates.

Measurement error

Measurement error in either the dependent or the explanatory variables can also give the researcher difficulty in precisely estimating the true relationships between constructs when they are measured imperfectly or inconsistently (Kennedy 2008). Typical examples of measurement error are sales or advertising figures, as all sales might not be reported across all channel or ad exposure measures, and do not correctly represent the true advertising mix employed by a firm or firms (e.g., Naik and Tsai 2000). Typically, measurement error in the dependent variables leads to an increase in the variance of the error term (i.e., residual error) but allows unbiased recovery of the effect of the measurement-error free independent variables. However, if the independent variables are measured with error, endogeneity arises that will bias the relationship and needs to be addressed. One OLS assumption (random error) is that the error term must not correlate with the explanatory variables, otherwise it will result in biased and inconsistent coefficient estimates. Suppose the true data-generating model is

$$y = x\beta + \varepsilon, \tag{3.1}$$

where,

y Firm Performance, e.g., sales,
x Marketing Strategy, e.g., online ad spend,
ε i.i.d. error term.

The researcher only observes sales (y) without error and online ad spend (x) with measurement error of unknown origin, $\dot{x}$:

$$\dot{x} = x + \eta, \eta \text{ is the measurement error,} \tag{3.2}$$

$$y = \dot{x}\beta + \upsilon, \upsilon \ \text{ i.i.d error term.} \tag{3.3}$$

As $\upsilon = \eta\beta + \varepsilon$, both x and υ are a function of η, making x endogenous. Generally, this biases OLS estimation of β toward zero, known as attenuation bias (Wooldridge 2010).

When there is correlation between the observed explanatory variable and its measurement, coefficient estimates will attenuate to zero and are a function of the variance of the explanatory variable relative to the variance of the measurement error. That is, measurement error in the explanatory variable (x, e.g., online ad spend) creates biased estimates, and could lead the researcher to conclude that online advertising has no effect on firm sales when in reality it does. If the researcher collects observations of dependent variables (y, e.g., sales) that are measured with error and where the error is not systematically related to the explanatory variables in the model, estimates from the model of interest will not be biased and this error will be captured by the error term as designed. However, measurement error in the dependent variable that is correlated with explanatory variables also results in endogeneity issues. Clearly, the researcher's model will only be as good as his or her ability to accurately and consistently measure the phenomenon of interest; otherwise, even the best-specified models will produce questionable results at best.

Approaches to addressing endogeneity

We will discuss six different methods to address endogeneity in empirical settings. Two methods require the researcher to have access to instruments that are strong and valid, often a tricky proposition. These methods are instrumental variables (IV) and the control function. We also discuss two instrument-free methods that do not require availability of such instruments but make certain distributional assumptions. These methods are latent instrumental variables (LIV) and Gaussian copulas. Researchers could also leverage field experiments, the fifth method discussed, to altogether avoid endogeneity in the data. Finally, a sixth approach is the structural econometric model. While the first four approaches augment a given reduced form model and the fifth approach is model-free, structural models are custom built to address endogeneity (Table 2).[2]

Instrumental variable

If other independent variable(s) are available, they could be leveraged to address the endogeneity issues. A potential instrument first must be correlated with the endogenous variable, and second, cannot be correlated with the error term (ε) in the focal equation (for example, in Eq. 1 in 1.1–1.3). The first condition describes the strength of the instrument, that is, how capable it is to potentially correct the endogeneity bias. An instrument with high (low) correlation with the

[2] A strong caveat is the assumptions needed for a structural model to be identified. Often, these result in models that will not fit a marketing strategy application.

Table 2 Approaches to addressing endogeneity in empirical data

Approach	Specification	Estimation	Appropriate use	Literature using approach
Instrumental variable	(4.1) $y = x\beta + \varepsilon$, ε i.i.d. error term (4.2) $x = z^{IV}\varphi + \tau$, where z^{IV} are the instrument(s).	• 2 stage least squares • (2SLS) • Maximum likelihood Generalized method of • moments (GMM) Bayesian estimation	An IV must 1) be correlated with the endogenous variable, and 2) cannot be correlated with the error term, (ε). The first condition describes the ability of the instrument to correct for the endogeneity of the equation. An instrument with high (low) correlation with the endogenous variable is a strong (weak) instrument. The second condition is referred to as the exclusion restriction, as the IV must not have the same issue as the original endogenous variable(s).	Stock et al. (2002); Kleibergen and Zivot (2003); Ataman et al. (2010); Van Heerde et al. (2013); Novak and Stern (2009); Kuksov and Villas-Boas (2008)
Control function	(5.1) $y = x\beta + \varepsilon$, ε i.i.d. error term. (5.2) $x = z^{CF}\varphi + \tau$, where z^{CF} is the instrument(s). Endogeneity correction occurs by adjusting the error structure of the model. Given that $E(x, \varepsilon) \neq 0$ the linear projection of ε on τ is given by (5.3) $\varepsilon = \rho\tau + \nu$, where $\rho = E(\varepsilon\tau)/E(\tau^2)$. Given $E(\tau\nu) = 0$ if follows that $E(z^{CF}, \nu) = 0$ resulting in (5.4) $y = x\beta + \rho\tau + \nu$ and $E(x, \nu) = 0$.	• Presuming data on x and z^{CF}, we can write $\tau = x - z^{CF}\varphi$ and estimate φ. This gives an estimate of $\hat{\tau}$ to substitute in eq. (6.4), which provides control function estimates, calculated by: • OLS	The control function approach is better suited to addressing endogeneity when the dependent variable is non-continuous. Main advantages of the control function approach include 1) relatively simple re-specification of the model through the introduction of a new regressor, as well as 2) the computational tractability this specification implies. Note that the introduction of a predicted τ in the second step is not the actual value of the exogenous explanatory variable. As a result, the researcher should instead bootstrap the standard errors of the model, or derive the specific forms of the standard two-step formulas applicable for their model if closed form solutions exist.	Petrin and Train (2010); Newey and McFadden (1994); Luan and Sudhir (2010); Ebbes et al. (2011); Wooldridge (2015); George et al. (2013); Luan and Sudhir (2010)
Latent instrumental variable	(6.1) $y = x\beta + \varepsilon$, ε i.i.d. error term (6.2) $x = z^{LIV}\pi + \tau$, where z^{LIV} are the latent categorical instrument(s).	• Maximum likelihood (closed form) • Bayesian, e.g. MCMC (with appropriate priors)	LIVs defined as unobserved categorical variables from a multinomial distribution, where the mean of the *j* th category is given by $\lambda_j > 0, \sum_j \lambda_j = 1, \begin{pmatrix} \varepsilon \\ \tau \end{pmatrix} \sim N\left(0, \begin{pmatrix} \sigma_\delta^2 & \sigma_{\delta\tau} \\ \sigma_{\varepsilon\tau} & \sigma_\tau^2 \end{pmatrix}\right)$ and $E\left(z^{LIV}, \varepsilon\right) = 0$ and $E\left(z^{LIV}, \tau\right) = 0$. It must be possible to linearly decompose the endogenous variable into separate exogenous and endogenous parts. Strong theoretical justification is still needed for the choice of LIV to correct endogeneity, and must be certain of two assumptions. 1) The endogenous explanatory variable should *not* be normally distributed, as the LIV approach exploits non-normality to separate the endogenous and exogenous parts of the compromised variable. 2) The error term must be approximately normal.	Ebbes et al. (2005); Abhishek et al. (2015); Grewal et al. (2013); Lee et al. (2014); Rutz et al. (2012); Rutz and Trusov (2011); Sonnier et al. (2011); Srinivasan et al. (2013), and Zhang et al. (2009)
Gaussian copula	(7.1) $y = x\beta + \varepsilon$, ε i.i.d. error term. (7.2) $y = x\beta + x^*\beta_{GC} + \tau$, τ i.i.d. error term. (7.3) $x^* = \Phi^{-1}(H(x))$ where x = the endogenous variable, x^* = the copula term, $(H(x))$ = empirical cumulative density (CFD) function of x, Φ^{-1} = the inverse normal CDF	• OLS for point estimate • Bootstraping standard errors with replacement • This provides a sample of point estimates of the coefficients of interest, wherein the standard deviations of these estimates are used as the standard error.	Like LIV, a key advantage includes a relatively simple re-specification of the model through the introduction of a new regressor. However, this often necessitates bootstraping the standard errors of the model and can only be accomplished when the DV is non-normal with a normal error term. Another advantage of the Gaussian copula approach is that it allows the researcher to correlate discrete and continuous variables, which LIV cannot, as well as handle "slope endogeneity" when the regressor is correlated with the random coefficient. An important consideration is that this approach assumes constant correlations between the endogenous regressor and the modeled random variables, which if violated, can yield biased results.	Park and Gupta (2012); Nelsen (2006); Balakrishna and Lai (2009); Danaher and Smith (2011); Kumar et al. (2014); Zhang et al. (2017)

Table 2 (continued)

Approach	Specification	Estimation	Appropriate use	Literature using approach
Field experiment	Presume there are ***s*** different levels of a single factor (treatment) under study where the response (outcome) for each ***s*** is a random variable. Let y_{ij} represent the j^{th} observation for each individual treatment, *i*, across an equal number of observations, *n*. The researcher can then describe the observations of the experiment as follows: (8.1) $y_{ij} = \mu + \tau_i + \varepsilon_{ij}$, where $i = 1, 2, \ldots, s$ and $j = 1, 2, \ldots, n$. y_{ij} is a random variable that denotes the *ij* th observation, μ is a parameter that denotes the overall mean common to all treatments, τ_i denotes i^{th} treatment effect, and ε_{ij} is the random error term. Typically, the researcher chooses the ***s*** treatments based on hypothesized relationships, leading to a fixed-effects model.	• ANOVA is most common. It partitions the Total Sum of Squares to provides a *F* -statistic for hypothesis testing that treatment effects are non-zero, ($\tau_i \neq 0$).	Although well-executed field experiments can lend plausible logic for the elimination of endogeneity concerns in the manipulated dependent variables. However, it can still be difficult completely rule out endogeneity concerns in general due to the numerous factors outside the control of both the focal firm and the experimenter. For example, even if the focal firm experiments with different price levels, the researcher cannot safely assume that a competitor is not responding to these different price levels, which once again biases potential inferences based on this response. Even if the firm runs an experiment manipulating their own treatments, this does not necessarily imply all other possible (e.g. omitted variables) have been controlled as one would in a "clean" laboratory experiment.	Johnson et al. (2017); Anderson and Simester (2004); Godes and Mayzlin (2009); Kuhfeld et al. (1994); Sen et al. (2006)
Structural model	Assume a general relationship (i.e., structure) between dependent variable (*y,* e.g., sales), explanatory variable (*x,* e.g. online ad spend), and other unobservable but influential variables (*z*), providing a stochastic economic model of a firm's sales function, *S*: (9.1) $S\ (x, z, \Theta)$ To account for common issues that lead to endogeneity problems, assume of a vector of unobserved characteristics (ε) directly into the firm's behavior function, *S*, to transform the stochastic economic model into an structural econometric model: (9.2) $y = S\ (x, z, \Theta, \varepsilon)$ Use economic theory to assume potential characteristics of a firm's behavior. For example, suppose a firm maximizes their sales function, *S*, subject to their known constraints (e.g., marketing budget) to obtain a sales function dependent on the observed and unobserved characteristics of the model: (9.3) $y = S_{max}\ (x, z, \Theta, \varepsilon)$ To estimate and recover the structural parameters of the model, Θ, assume joint population distributions for the non-structural elements of the model to derive a joint distribution of the observed data: (9.4) $h\ (x, z)$	• The choice of an estimation technique is part informed by the researcher's choice of functional forms and distributional assumptions of the model, as well as the quality and quantity of available observations. • Maximum likelihood (closed form if possible) • Bayesian, e.g. MCMC, Gibbs sampling (with appropriate priors)	The assumptions about the joint distributions of the nonstructural elements of the model should be guided by economic theory relevant to the environment of study. The goal is to be able to estimate the parameters of Θ from the structure specified by the researcher in Eq. (8.3), and to do provide consistent estimates of Θ using the available data. Thus, the researcher mitigates endogeneity problems by utilizing a structural approach that explicitly accounts for the data generating model (and error) based on the economic and statistic assumptions that derive a joint density for the observed data. The assumptions and structure explicitly placed on the model depend on the context of the research and more importantly, the question(s) the researcher seeks to answer. Structural models are adept at examining possible hypothetical outcomes in a model due to managerial policy changes, as the coefficients of the model are policy-invariant because they depend on the underlying behavior and optimization assumptions of the model, rather than the observed empirical relationships of the data. However, unrealistic or unfeasible assumtions may yield results with poor generalizability.	Lucas (1976); Berry (1994); Kadiyali et al. (2000); Dube et al. (2002); Chintagunta et al. (2003, 2004, 2006); Erdem and Keane (1996); Gatignon and Xuereb (1997); Hoffman and Novak (1996); Sun (2005)

endogenous variable is a strong (weak) instrument. The second condition is generally referred to as the exclusion restriction (Angrist et al. 1996). Thus, the prerequisite for the instrument is that it must not have the same issue as the endogenous variable otherwise it is considered a "poor" instrument. By employing this approach, the researcher decomposes the variation in the endogenous variable into two parts: one part correlated with the error term, and a second part not correlated with the error term used to estimate the model, broadly speaking as follows.

Specification Assuming suitable instrument(s) are available, the model[3] is given by

$$y = x\beta + \varepsilon, \tag{4.1}$$

$$x = z^{IV}\varphi + \tau, \tag{4.2}$$

where,

y Firm Performance, e.g., sales,
x Marketing Strategy, e.g., online ad spend,
z^{IV} the instrument(s), e.g., online ad costs differences across markets, "Seattle Hotels" vs. "Portland Hotels",[4]

ε and τ = i.i.d. error terms.

Estimation Equation (4.1) and (4.2) can either estimated separately for linear models (so called 2-stage least square or 2SLS) or simultaneously using maximum likelihood (Rossi 2014), generalized method of moments (Stock et al. 2002) or a Bayesian approach (Kleibergen and Zivot 2003; Ataman et al. 2010). For further reading on methodology, see Wooldridge (2010), and Van Heerde et al. (2013). See, for example, Novak and Stern (2009), and Kuksov and Villas-Boas (2008) for substantive application in marketing literature. Note that multiple packages in R exist that allow interested researchers easy implementation of the IV approach.[5]

Appropriate use To employ the IV method effectively, the researcher should have strong theoretical reason or empirical evidence that one (or more) explanatory variables are actually correlated with the error term (i.e., endogenous), but an inability to collect the actual missing explanatory variable directly (e.g., managerial decision making). Endogeneity in online ad spend could be addressed by using online advertising costs in similar but different markets as IVs. The idea is that changing costs of advertising in different but related markets will cause similar, but exogenous, variation in advertising spend across retailers serving different market segments, in this case utilizing costs for "Hotels in Portland" as an IV for costs of "Hotels in Seattle," the market of interest. These costs may drive ad spend in an adjacent market similarly to the way it drives ad spend in the market of interest, and thus those ad costs can be used as IVs as they are not correlated with the error term (Dinner et al. 2014).

In the event of multiple endogenous regressors, the researcher must likewise have at their disposal an effective instrument and corresponding theoretical justification for each compromised explanatory variable that meets both the strength and exclusion requirements, which in practice is no small feat (Papies et al. 2017). Correctly chosen IVs are also useful for binary endogenous regressors as the 2SLS procedure makes no assumptions as to the distributional nature of the regressor, such as the effect of loyalty program membership (endogenous due to customer self-selection) on share of wallet (Leenheer et al. 2007). In the IV approach, predicted values of the compromised variable are computed with only exogenous information (stage 1) and then these exogenously predicted values are used in lieu of the endogenous variable (stage 2). The predicted values calculated in "stage 1" of 2SLS (or similar techniques) are no longer directly correlated with the error term thus addressing the endogeneity concern. The researcher may be tempted to use past iterations (i.e., lagged values) of an endogenous variable as a potential instrument, however these previous values only have potential as instruments if the researcher is certain unobserved shocks are limited to the period of estimation (Rossi 2014; Papies et al. 2017). However, if the IV used is not itself strong and valid, then the researcher's "solution" simply introduces more error into the model and will fail to resolve the original problem.

One of the most critical issues in using the IV approach is the availability of suitable instruments. One test typically used is the Hausman test (1978). On issue with the Hausman test and other tests that are derived from it is the notion that one needs to have at least on valid instrument to do the test. To implement the Hausman test one estimates Eq. (4.2) and calculates $\hat{\tau} = x - z^{IV}\hat{\varphi}$, where $\hat{\varphi}$ is the estimated coefficient. Now one estimates

$$y = x\beta + \delta\hat{\tau} + \nu. \tag{4.3}$$

If δ is significant one can conclude that x is endogenous.[6]

[3] For ease of exposition we do not include any exogenous variables in the model formulations.
[4] The key idea is to leverage variation independent of the variable of concern. For example, online spend (ad costs) for Portland in our case when the focal market is Seattle.
[5] For 2 Stage Least Squares (SLS) please see: https://www.rdocumentation.org/packages/AER/versions/1.2-5/topics/ivreg. For simultaneous estimation please see https://cran.r-project.org/web/packages/ivmodel/ or https://cran.r-project.org/web/packages/ivpack/.

[6] The R package for 2SLS estimation called "ivreg" (see Footnote 2) also provides a Hausman test.

Building on this test, Hahn and Hausman (2002) provide an approach to test the both exogeneity and strength of available instruments. The test requires to estimate two models, the two stage model given by (4.1) and (4.2) and a reverse model given by

$$x = y\lambda + \varepsilon, \varepsilon \text{ i.i.d.error term,} \tag{4.4}$$

$$y = z^{IV}\varphi + \tau, \text{where } z^{IV} \text{are the instrument(s).} \tag{4.5}$$

In this specification $1/\lambda = \beta$. The test compares the estimate of $\beta_{forward}$ from the forward model (given by 4.1 and 4.2) and $\beta_{reverse}$ from the model given in (4.4) and (4.5). Please, see Hahn and Hausman (2002) for details. Additionally, the researcher can bolster their theoretical reasoning for an IV by considering the Sanderson-Wodmeijer multivariate F-test to inform the strength of their chosen instrument(s), and report it along with results (Sanderson and Windmeijer 2016). Related, but perhaps more controversial tests for the exclusion restriction may include the Sargan test and the Hansen test (Sargan 1958; Hansen 1982),[7] which attempts to test whether an IV is exogenous, but can only be used when there are more IVs than endogenous regressors (i.e., an over-identified model). For further reading, see Wooldridge (2010, p. 135).

Control function

This approach derives a proxy variable that conditions on the part of the observed endogenous regressor that depends on the error term. In spirit, the control function approach is close to the IV approach discussed above. After successfully implementation, the remaining variation in the endogenous variable is no longer compromised and estimates of coefficients are consistent (Petrin and Train 2010). Like the IV approach above, the control function approach does require researchers to have access to instruments. Since the researcher need only add new regressors to the model specification, the approach is viable in many instances. However, recovering the proxy variable is not always possible. For linear models, the control-function approach and the 2SLS IV approach are equivalent. For non-linear models, the control-function approach offers an alternative model to simultaneous estimation of the IV model. Utilizing a linear model, a control function approach may take the following form.

Specification

$$y = x\beta + \varepsilon, \tag{5.1}$$

$$x = z^{CF}\varphi + \tau, \tag{5.2}$$

where,

y	Firm Performance, e.g., sales.
x	Marketing Strategy, e.g., online ad spend,
z^{CF}	the instrument(s), ad costs differences across markets, "Seattle Hotels" vs. "Portland Hotels",[8]
ε and τ	i.i.d. error terms.

In the control-function approach, the endogeneity correction occurs by adjusting the error structure of the model. Given that $E(x, \varepsilon) \neq 0$ the linear projection of ε on τ is given by

$$\varepsilon = \rho\tau + \nu, \tag{5.3}$$

where,

$$p = E(\varepsilon\tau)/E(\tau^2).$$

Given $E(\tau\nu) = 0$ if follows that $E(z^{CF}, \nu) = 0$ resulting in

$$y = x\beta + \rho\tau + \nu \text{ and } E(x, \nu) = 0. \tag{5.4}$$

Estimation Given that we have data on x and z^{CF}, we can write $\tau = x - z^{CF}\varphi$ and estimate φ, giving us an estimate $\hat{\tau}$ to substitute into eq. (6.4). The estimates of eq. (6.4) after the substitution are the control function estimates, calculated with OLS. For further reading on methodology, see Wooldridge (2010, 2015), and Ebbes et al. (2011) a well as Petrin and Train (2010) for substantive application in marketing research. As far as we can tell at this point no general R package exists for the implementation of the control function approach.[9]

Appropriate use The control function approach is generally well suited to addressing endogeneity when the dependent variable is non-continuous (Papies et al. 2017). Main advantages of the control function approach include relatively simple re-specification of the model through the introduction of a new regressor, as well as the computational tractability this specification implies (Petrin and Train 2010). This computational tractability is also useful for handling "limited" dependent variables that are not fully continuous, such as binary (e.g., introduce a loyalty program or not), multinomial (e.g., advertising channel choice among possibilities), discrete and/or truncated variables (e.g., non-negative ad spend), among others (Andrews and Ebbes 2014). It is also straightforward to accommodate interaction terms where one or both of the interacted variables are endogenous, or similarly, squared endogenous terms (Papies et al. 2017; Wooldridge 2015). A researcher could employ the same technique with slight

[7] The R package "ivreg" provides the Sargan test for 2SLS estimation. For Generalized Methods of Moments (GMM) estimation the R function "sargan" calculated the Hansen-Sargan test, please see: https://www.rdocumentation.org/packages/plm/versions/1.6-5/topics/sargan.

[8] The key idea is to leverage variation independent of the variable of concern. For example, online spend (ad costs) for Portland in our case when the focal market is Seattle.

[9] Please note that Kenneth Train as software available on his website, albeit only for the Mixed Logit Model: https://eml.berkeley.edu/~train/software.html.

modification to the first stage regression to separate the effect of the interacted variable and the instrument on the endogenous regressor, or consider the squared endogenous regressor as an interaction with itself, and then augment the next stage regression with those fitted residuals per the usual control function approach (Wooldridge 2015, p. 428). Occasionally, recovering estimates can prove more difficult in non-linear models. However, because the introduction of $\hat{\tau}$ in the second step is a predicted estimate, and not the actual value of the exogenous explanatory variable, the standard errors obtained in the second step do not account for this extra variation. As a result, the researcher should instead bootstrap the standard errors of the model, or derive the specific forms of the standard two-step formulas applicable for their model if closed form solutions exist (Newey and McFadden 1994; Luan and Sudhir 2010).

Latent instrumental variable

A general issue of instrument-based methods as discussed above is the strength and validity of the chosen (or available) instruments (Kennedy 2008). Often, available instruments are neither strong nor valid and thus are not able to correct for underlying endogeneity concerns. The method of latent instrumental variables (LIV, Ebbes et al. 2005) addresses the lack of suitable instrument(s) by utilizing a latent variable to estimate parameters when endogeneity is present, i.e., the latent instrument is estimated during the procedure and does not need to be available to researchers. To state this more succinctly, the LIV methods does not require the researcher to have access to instrumental variables as necessary when using instrument-based methods such as IV or control function. As with a standard instrumental variable approach, the endogenous explanatory variable is decomposed into an exogenous part and an endogenous error term. When utilizing a latent instrument, the exogenous term is a latent discrete variable and the model parameters are identified and estimated via maximum likelihood methods, similar to the following.

Specification The LIV is given by

$$y = x\beta + \varepsilon, \tag{6.1}$$

$$x = z^{LIV}\pi + \tau, \tag{6.2}$$

where,

y Firm Performance, e.g., sales,
x Marketing Strategy, e.g., online advertising,
z^{LIV} latent instrument(s),
ε and τ i.i.d. error terms.

In the LIV approach, the latent instrumental variables are defined as unobserved categorical variables arising from a multinomial distribution where the mean of the jth category is given by $\lambda_j > 0, \sum_j \lambda_j = 1$, $\begin{pmatrix} \varepsilon \\ \tau \end{pmatrix} \sim N\left(0, \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\tau} \\ \sigma_{\varepsilon\tau} & \sigma_\tau^2 \end{pmatrix}\right)$ and $E(z^{LIV}, \varepsilon) = 0$ and $E(z^{LIV}, \tau) = 0$.

Estimation Maximum Likelihood most efficiently estimates the LIV model when the model specification is closed form and when there is sufficient data for estimation or by Bayesian estimation when appropriate prior distributions are choses even under sparse data conditions. For further reading on methodology, see Ebbes et al. (2005), and Sonnier et al. (2011), and Lee et al. (2014) for a substantive application in marketing research. Note that an R package (REndo) exists for the LIV method.[10]

Appropriate use As with the use of a traditional (non-latent) instrument, the researcher assumes it is possible to linearly decompose the endogenous explanatory variable into separate exogenous and endogenous parts. As a result, the researcher must still provide strong theoretical justification as to the presence of endogeneity in the original specification, as well as for the choice of LIV to correct it. The researcher must also be certain of two characteristics of the model in order to abide by the assumptions needed to employ a latent instrumental variable. First, the endogenous explanatory variable should not be approximately normally distributed, as the LIV approach precisely exploits this non-normality to separate the endogenous and exogenous parts of the compromised variable. Second, it is also necessary for the researcher to examine that the error term, in contrast to the endogenous variable(s), is itself approximately normally distributed. If the endogenous variable is normally distributed, and/or the error term is not, then the LIV approach is not feasible and the researcher must examine other options to address endogeneity concerns. In the LIV framework Ebbes et al. (2005) propose a Hausman-type test for endogeneity which compares the basic OLS estimate, β_{OLS} with the LIV estimate, β_{LIV}. A benefit of the proposed LIV test is that it does not require any instruments as it compares the LIV estimate to an OLS estimate.

Gaussian copula

Similar to the LIV approach, the Gaussian copula approach is a statistical, instrument-free method (Park and Gupta 2012). Instead of leveraging instruments this method models the joint distribution of the endogenous variable and the error term and makes inferences on the model parameters by maximizing the likelihood from the joint distribution. The approach requires treating the

[10] Please see: https://cran.r-project.org/web/packages/REndo/index.html.

endogenous variable as a random variable from a non-normal marginal population distribution and uses a copula to correlate it with a normal error term. After such a treatment the remaining variation in the original endogenous variable is no longer compromised and estimates of coefficients are consistent. Since the researcher once again only needs to add new regressors to the model specification, the approach is also viable in numerous contexts. Utilizing a linear model, a Gaussian copula function approach may take the following form.

Specification As in the control function approach, the Gaussian copula approach augments the original equation (below) with a new term to control for endogeneity.

$$y = x\beta + \varepsilon, \tag{7.1}$$

where,

- y Firm Performance, e.g., sales,
- x Marketing Strategy, e.g., online ad spend,
- ε i.i.d. error term.

The researcher keeps the original endogenous variable, x in our example, and augments (7.1) with a copula term x^* and its corresponding parameter, β_{GC}.

$$y = x\beta + x^*\beta_{GC} + \tau, \tag{7.2}$$

$$x^* = \Phi^{-1}(H(x)), \tag{7.3}$$

where,

- x the endogenous variable,
- x^* the copula term,
- $H(x)$ empirical cumulative density (CFD) function of x,[11]
- Φ^{-1} the inverse normal CDF,
- τ i.i.d. error term.[12]

Estimation Although the researcher can now consistently estimate Eq. (7.2) and get an unbiased estimate of the parameter of interest, β, the OLS standard errors are not correct because x^* is estimated and not directly observed. Typically, this is resolved by bootstrapping the standard errors with replacement to produce a sample of point estimates of the coefficients of interest, wherein the standard deviations of these estimates are used as the standard errors (Park and Gupta 2012). Note that the estimate for the Gaussian Copula parameter β_{GC} allows to test for the presence of endogeneity directly. For further reading on methodology, see Nelsen (2006), Balakrishna and Lai (2009), and Danaher and Smith (2011), as well as Kumar et al. (2014), and Zhang et al. (2017) for substantive applications and extensions in marketing research.

Appropriate use As with the LIV function approach, a key advantage of this approach includes a relatively simple re-specification of the model through the introduction of a new regressor, but often necessitates bootstrapping the standard errors of the model. Likewise, implementing the Gaussian copula approach for addressing endogeneity can only be accomplished when the dependent variable is non-normal with a normal error term (Danaher and Smith 2011). If both the endogenous regressor and the error term are approximately normal, the researcher should not employ a Gaussian copula approach as the model will not be able to separate the endogenous variation and suffer from identification problems. Another advantage of the Gaussian copula approach is that it allows the researcher to correlate discrete and continuous variables as well as handle "slope endogeneity" when the regressor is correlated with the random coefficient (Park and Gupta 2012). An important consideration is that this approach assumes constant correlations between the endogenous regressor and the modeled random variables, which, if violated, can yield biased results.

Field experiments

In a sense, every researcher that assumes a factor under investigation varies independently of an error term "effectively views their data as coming from an experiment" (Harrison and List 2004, p. 1004). As we have discussed thus far, the independence of a variable from the error term may be a matter of assumption, gleaned from corroborating evidence, or even built into the data collection the researcher chooses to employ. Rather than make such an assumption, a researcher may choose to address endogeneity directly through the research design choice when feasible.

Experiments are often presented as the gold standard to create causal insights as they allow for manipulation of variables of interest in controlled settings (Johnson et al. 2017). In particular, the design and implementation of controlled field experiments are increasingly utilized because they allow the researcher to "exogenously" control hypothesized independent variables and examine their effect on the phenomenon of interest in a setting that is more generalizable, yet complimentary to, a pure lab setting. As with IVs and LIVs, the goal of the controlled field experiment is to create an appropriate counterfactual for a given treatment effect (e.g., a different online advertising strategy to be tested), in this case by directly

[11] Park and Gupta (2012) give more details how to non-parametrically estimate the density of the marginal distribution of the endogenous variable, p.570–572.

[12] In more detail, $\tau = \sigma_\varepsilon \sqrt{1-\rho^2}\varpi_2$ where ρ is the correlation coefficient, $\varpi_2 \sim N(0, 1)$ and σ_ε is the standard deviation of ε.

constructing a control group through randomization of treatments across subjects.[13]

Specification Suppose we have s different levels of a single factor (treatment) under study where the response (outcome) for each s is a random variable. Let y_{ij} represent the j^{th} observation for each individual treatment, i, across an equal number of observations, n. The researcher can then describe the observations of the experiment as follows

$$y_{ij} = \mu + \tau_i + \varepsilon_{ij}, \tag{8.1}$$

where,

- y_{ij} a random variable that denotes the ij^{th} observation,
- μ a parameter that denotes the overall mean common to all treatments,
- τ_i the i^{th} treatment effect,
- i 1, 2, …, s,
- j 1, 2,…, n.
- ε_{ij} the random error term.

Typically, the researcher chooses the s treatments based on hypothesized relationships, leading to a fixed-effects model.

Estimation In such a model, ANOVA is the most common analysis to determine whether a manipulated variable affected the dependent variable. To begin, the treatment effects, τ_j, are typically specified as deviations from the overall mean, μ.

$$\sum_{i=1}^{s} \tau_i = 0 \tag{8.2}$$

For the i^{th} treatment, define y_i^* as the total of the observed data and $\overline{y}_i^*$ to denote the average of the observations, and relatedly $y..$ as the grand total and $\overline{y}..$ as the grand mean of all observations.

$$y_i^* = \sum_{j=1}^{n} y_{ij}, \text{ where } \overline{y}_i^* = y_i^*/n \text{ and } i = 1, \ldots, s, \tag{8.3}$$

$$y.. = \sum_{i=1}^{s} \sum_{j=1}^{n} y_{ij}, \text{ where } \overline{y}.. = y../n \text{ and } N = sn. \tag{8.4}$$

The researcher then tests for the equality of treatment means, which can be tested by following hypotheses:

$$H_0 : \tau_1 = \tau_2 = \ldots = \tau_s = 0, \tag{8.5}$$

$$H_1 : \tau_i \neq 0 \text{ for at least one treatment}, i. \tag{8.6}$$

If the null is true, then the researcher can conclude that changing the levels of a factor (treatment) has no effect on the mean response. To test these hypotheses, ANOVA will partition the variability of the data and then the researcher test the null hypothesis with an F-statistic (after appropriately adjusting for degrees of freedom). If F_0 is large, then the researcher should reject $H_0 : \tau_1 = \tau_2 = \ldots = \tau_s = 0$, indicating the treatment effects of the manipulated variables are statistically significant. The R Stats package includes ANOVA for R.[14]

Appropriate use Although well-executed field experiments can lend plausible logic for the elimination of endogeneity concerns in the manipulated independent variables, it can still be difficult to see how even a field experiment can be 100% free from endogeneity concerns to the numerous factors outside the control of both the focal firm and the experimenter. For example, even if the focal firm experiments with different price levels, the researcher cannot safely assume that a competitor is not responding to these different price levels, which once again biases potential inferences based on this response. Even worse, many of the new tools available to marketers to reach customers in the digital age such as social media ads, search ads, and display ads, are served by the platforms using targeting algorithms to ensure relevance to consumers. Even if the firm is willing to experiment with, say different ad copies, the firm's ad is shown in a competitive context (typically not available to the advertiser) and, making matters worse, the advertising platform uses targeting algorithms. In a recent paper, Johnson et al. (2017) detail this issue in the case of display advertising. In short, even if the firm runs an experiment manipulating their own treatments (e.g., display ads), this does not necessarily imply all other possible variables have been controlled for as one would expect in a "clean" laboratory experiment.

[13] The goal of a field experiment is to be able to compare outcomes directly between treated and non-treated groups to determine the effect of the treatment, e.g. a given marketing strategy. In non-experimental data, the researcher cannot distinguish between a treatment and control group as the use of a particular strategy is generally non-random, but rather self-selected by the firm to implement, making the choice to implement a strategy, and thus the "effect" of the strategy, endogenous. To remedy potential self-selection bias in observational data, it may be possible to "match" firms exhibiting a given strategy with firms that do not, but otherwise appear very similar on multiple criteria through propensity score matching. This idea is to determine the probability of treatment assignment, for example, the propensity to start a loyalty program, conditional on observed baseline characteristics, e.g. firm size, customer demographics, and so forth. This allows the researcher to design and analyze an observational study to mimic the characteristics of a randomized controlled trial between the observed treated group and a matched non-treated group (Rosenbaum and Rubin 1983). In practice however, this may not always be feasible due to data constraints on which to produce a propensity score for each observation (see Austin 2011, p.414–415). For further reading on methodology, see Austin (2011), Heckman (1979), Rosenbaum and Rubin (1983), Guo and Fraser (2010), and the PSMATCH2 STATA module from Leuven and Sianesi (2003). For recent substantive applications and extensions in marketing research see Kumar et al. (2016), Ballings et al. (2018), and de Haan et al. (2018).

[14] Please see: https://stat.ethz.ch/R-manual/R-devel/library/stats/html/00Index.html.

A key issue with the field study approach is that the researcher needs to find a firm willing to collaborate. A major shortcoming of this approach as it related to marketing strategy research is that firms are typically unwilling to do large-scale experiments on large strategic issues (e.g., hiring and firing CMO, changing the firm's marketing orientation, etc.).[15] Even if the researcher is able to find a willing firm, another key issue in today's marketplace is that control conditions are not easy to create (Johnson et al. 2017). For example, competitor firms will continue to market to the customers in both the control and the treatment condition. For exposure-based marketing, it often means that in the control condition (i.e., no marketing from the focal firm) the consumer is now exposed to additional competitive marketing activity.

Structural econometric models

In contrast to descriptive models, structural models aim to recover the economic parameters of a joint distribution between x (independent) variables and y (dependent) variables of interest, $f(x, y)$. Correctly executed, the researcher mitigates endogeneity problems by specifying the economic "structure" (i.e., assumptions driven by theory) that generates the observational data and the plausible realizations of x and y. Doing so allows the researcher to recover corresponding parameters of interest to make causal statements and perform counterfactual analysis (Chintagunta et al. 2006). A necessary first step is to determine the theoretical reasoning that places restrictions on the outcomes, y, and potential economic drivers, x, in a prospective model. A researcher may start by assuming basic constraints on utility and demand for a given product as well as prices and income as follows.

Specification The researcher may assume a general relationship (i.e., structure) based on economic theory between total sales (y), online advertising expenditure (x), and other unobservable but influential variables (z) such as customer characteristics, competitor prices, or ad auction results, providing a stochastic economic model of a firm's sales function, S:

$$y = S(x, z, \Theta), \tag{9.1}$$

where,

$S(\cdot)$ a known sales function (determined by the researcher),
x marketing strategy, e.g. online advertising expenditure,
z a vector of unobserved variables, e.g. ad auction results,
Θ a set of unknown parameters.

Economic theory by itself may not provide sufficient information for the researcher to estimate the parameters of interests, Θ, nor might the economic model be able to perfectly rationalize the entirety of the observed data. Consequently, the researcher may assume statistical error terms to account for common issues that lead to endogeneity problems such as unobserved explanatory variables and/or errors in variables. This is explicitly addressed though the inclusion of a vector of unobserved characteristics (ε) directly into the firm's sales function, thereby transforming a stochastic economic model into an structural econometric model

$$y = S(x, z, \Theta, \varepsilon). \tag{9.2}$$

The researcher also uses economic theory to assume potential characteristics of a firm's behavior. For example, suppose a firm maximizes their sales function, S, subject to their known constraints (e.g., marketing budget) to obtain a sales function dependent on the observed and unobserved characteristics of the model

$$y = S_{\max}(x, z, \Theta, \varepsilon). \tag{9.3}$$

Since the researcher is interested in estimating and recovering the structural parameters of the model, Θ, that inform the relationship of online ad expenditure and total sales, he or she will generally assume joint population distributions for the non-structural elements of the model to be able to derive a joint distribution of the observed data

$$h(x, z). \tag{9.4}$$

The assumptions about the joint distributions of the non-structural elements of the model (y, x, z) should be guided by economic theory relevant to the environment of study. For example, the researcher may specify that online ad expenditure must be greater than zero, or that unobserved ad effectiveness increases at a decreasing rate as potential customers get tired of repetitive ad exposure (i.e., wear-out effect). The goal is to be able to estimate the parameters of Θ from the structure specified by the researcher in the formation of their model to provide consistent estimates of Θ using the observed data.

Estimation The choice of an estimation technique is part informed by the researcher's choice of functional forms and distributional assumptions of the model, as well as the quality and quantity of available observations. Larger data sets naturally provide greater statistical power and parametric flexibility, but are not necessarily available to the researcher addressing their particular domain of interest. Some distributions may make for mathematically tractable analysis and estimation, but may also be unrealistic (e.g., normal but unbounded competitor price distributions). If a researcher is willing to assume (specify) the complete distribution, conditional moments or maximum likelihood estimation of parameters is possible because the model implies the conditional distribution of the observed

[15] We thank an anonymous reviewer for raising this point.

endogenous variables given the exogenous variables. An important consideration for the researcher employing a structural econometric model is that they must "first use economics and statistics to demonstrate that the relevant economic quantity or comparative static effect can be identified using the available data and estimation technique" Reiss and Wolak 2007, p. 4291). The main point of a structural model is to model the underlying process and thus avoid the need for instruments for the particular issue at hand. For example, a model of forward-looking consumer behavior includes a model of consumers' expectations of future prices to inform whether a consumer should buy now or wait for a future period with a preferred price. Naturally, other endogeneity issues arising in the model that are not in the focus would also need to be addressed and often are through IVs. Particularly when examining simultaneous equations (e.g. supply and demand functions), this necessitates sufficient exogenous variation that may come from instrumental variables that supplement the economic and statistical structure of the model. For example, Chintagunta et al. (2003) use wholesale prices as an IV for endogenous retail prices to help identify and estimate parameters of store-level demand functions using retail stores sales data. Depending on the (joint) distributional assumptions of the parameters of the structural model, Bayesian estimations using Markov Chain Monte Carlo and Gibbs sampling can be employed when the mathematical form of the models do not provide closed form solutions for conditional moments. For further reading on methodology and substantive applications in marketing researcher, see Lucas (1976), Berry (1994), Kadiyali et al. (2000), Dubé et al. (2002), and Chintagunta et al. (2003), (2004), and Reiss and Wolak (2007).

Appropriate use A key reason to explicitly use economic theory in the design of analysis is to describe how institutional and economic conditions affect relationships between y and x in order to make causal statements about estimated relationships, or use them to perform counterfactual analysis (Reiss and Wolak 2007). As such, structural econometric models are adept at examining possible hypothetical outcomes due to managerial policy changes (Sun 2005), as the coefficients of the model are policy-invariant because they depend on the underlying behavior and optimization assumptions (e.g., firm behavior) of the model, rather than the observed empirical relationships of the data (Lucas 1976). Often, economic and statistical assumptions are made to reflect economic realities, rationalize observed data, or simplify estimation (Reiss and Wolak 2007). If the researcher can make strong theoretical arguments as to the relationship between observed and unobserved variables, then they may feel justified in imposing these theoretical relationships through the empirical specification of their structural model to directly address the endogeneity present in the reduced form model (Chintagunta et al. 2006). Even with parameters of the demand model and equations specifying firm behavior, the researcher may not have access to all variables of consequence on both the demand and supply side equations (e.g., data on all competitor behavior), rendering the ability to simulate firm behavior difficult at best. Since structural models necessitate relatively strong assumptions about the underlying behavior and optimization of economic actors, if these assumptions are flawed or overly restrictive, results of the structural model may be misleading or non-generalizable (Chintagunta et al. 2006).

Guidelines and considerations for strategy researchers

The presence of endogeneity in a researcher's model can potentially invalidate casual claims as we have discussed earlier in this manuscript. By nature, this issue is not easily dismissed when using observational data simply based on arguments or statistical evidence alone, and as a result, any researcher should be cognizant of these issues and lend significant thought to mitigating its risks. However, addressing potential endogeneity often requires placing additional assumptions and conditions on the model, and if done haphazardly, may "make the problem worse" (Papies et al. 2017, p.619). Not only could correcting for endogeneity in a researcher's model result in inferior fit both in- and out-of-sample even when well implemented (Ebbes et al. 2011), but poorly addressing endogeneity (e.g., a poor IV) can still result in coefficients as invalid as the ones derived from the original model (e.g., Rossi 2014).

Nonetheless, addressing endogeneity is a growing concern among marketing academics as evidence of the growing number of papers published annually in the last 20 years (Fig. 1, Panel A), yet this body of research directly addressing the issue remains an overall small proportion of extant literature (Fig. 1, Panel B). Because endogeneity may arise from many origins within a study's design, we discuss four general guidelines for marketing strategy researchers and summarize the six major approaches to addressing endogeneity to encourage greater consideration of these issues when undertaking any new research (Table 3).

Guideline 1: Rely on theory

The consequences of endogeneity are serious enough to warrant careful considerations of a multitude of possible causes in the study design, and ignoring the possibility of endogeneity may lead to misleading and incorrect findings. This potential is compounded by the likelihood that the magnitude and direction of the correlation between the error term and the endogenous explanatory variable may be positive or negative, and is dependent on the context of study. As a result, the researcher is well served to spend considerable time on the theoretical framework for two main reasons. First, the nomological framework and phenomena of study will provide crucial guidance as to the

Table 3 Considerations for addressing endogeneity

Approach	Technical difficulty	Data requirements	Study implementation difficulty	General considerations
Instrumental variable	Low	High	High	If a suitable IV is available, this approach is very effective in addressing endogeneity. However, the difficulty lies in finding an instrument that is strong and valid. In practice it is often difficult to find an IV that meets these conditions and does not suffer from the same endogeneity problem as the original model, and often result in estimates with large standard errors.
Control function	Moderate	High	High	This approach derives a proxy variable that conditions on the part of the observed endogeneous regressor that depends on the error term. If this can be done, the remaining variation in the endogenous variable is no longer endogenous and estimation is consistent. It is equivalent to 2SLS IV-approach in linear models, and an alternative model to simultaneous estimation of the IV model in non-linear models. Since the research need only add new regressors to the demand specification, the approach is viable. However, recovering the proxy variable is not always possible.
Latent instrumental variable	Moderate	Low	Moderate	The use of modeling a latent variable to account for regressor-error dependencies circumvents the instrument availability, weakness, and validity issues of standard IV approaches. Due to this, the LIV approach is useful in "sparse" data environments (i.e. infrequent observations) and does not compromise the precision of coefficient estimates as weak IVs are prone.
Gaussian copula	Moderate	Low	Moderate	Similar to the control function approach, employing a gaussian copula involves introducing a new term to the model specification. This terms controls for the correlation between the error term and the endogeneous regressor, and allows for the equation to be consistently estimated. However, because copula term is an estimate quantity, the OLS standard errors are incorrect, and instead must be estimated by another means, such as bootstrapping.
Field experiment	Low	High	High	If implemented as designed, field experiments can effectively address endogeneity concerns by manipulating and controlling explanatory variables of interest. However, field experiments may easily suffer from measurement error and unobserved variable bias due to field conditions outside of a labratory setting. In managerial settings, persuading firms to experimentally manipulate their behavior or is often unfeasible or unwanted, while the behavior of competitors remains unchanged and therfore outside the control of the experiment.
Structural Model	High	High	High	Structural model specification requires very strong assumptions about actor behaviors with respect to the supply and demand functions, as well as very high demands on data for estimation. These models can be excellent for testing theoretical boundary conditions and similations of firm behavior. In practice, obtaining sufficient data (e.g. competitor market behavior) for tighly parameterized models can lead to necessary simplifications that reduce applicability for managerial research.

most appropriate study design for the research question, as well as the potential variables to be collected/included to help avoid potential endogeneity to begin with. Second, by lending careful thought to the origin of the portion of variance in the suspected independent variable that is potentially endogenous, strong theoretical reasoning as to the presence or absence of endogeneity will help to guide both potential methods for addressing this concern, as well as yield a stronger nomological framework for the study in question. By relying on theory, the researcher will have a stronger study design to provide a better argument as to the necessity for the inclusion of an IV, for example, or a particular methodological choice due to an inability to collect other potentially important explanatory variables. Because of the multiple potential options for addressing endogeneity, the researcher must substitute one set of assumptions and constraints (e.g., an independent variable is endogenous) with another set (e.g., an IV is strong and valid), and thus must rely on sound theoretical reasoning to argue which approach is best.

Guideline 2: When in doubt, gather more data

As a common source of endogeneity in marketing studies is that of omitted variables (Germann et al. 2015), careful thought to identify and collect data on potential variables that can mitigate endogeneity concerns is time well spent. In the presence of a convincing argument for the possibility of endogeneity in the model, the researcher's first course of action should be to identify, measure, and include the possible omitted variable(s) in the existing model rather than immediately choose another more convenient method to address these concerns (Rossi 2014). Extending cross-sectional study to longitudinal panel data provides a straightforward way to introduce firm level and time varying controls through fixed effects, particularly when these potential variables are not of theoretical interest, but can nonetheless compromise a study from a statistical standpoint if omitted. Even still, in many contexts of managerial interest, it may be implausible to identify and measure all possible controls to mitigate endogeneity, and the researcher should still rely on sound theoretical reasoning beyond simply including control variables alone.

Guideline 3: LIV or Gaussian copula is often most feasible

Considering that in order for a variable to be suitable for use as an instrument it must be both a strong predictor of the independent variable as well as exogenous at the same time, the theoretical justification that makes an instrument valid (i.e., exogenous) also argues that it is weak (Rossi 2014). As a result, researchers have sought other methods to address this concern. The latent instrumental variable (LIV) approach as well as the Gaussian Copula approach provide a feasible alternative to finding and employing a traditional instrument that may be susceptible to the same problem as the original regressor. By specifying a latent (unobserved) instrument either via the LIV or the copula method, the researcher is able to "account for regressor-error dependencies and, as such, circumvent the issues of instrument availability, weakness, and validity" (Rutz et al. 2012, p. 308). Since the LIV and copula specification exploits non-normality in the explanatory variable, the researcher must be certain this condition is met along with normality in the error terms (Ebbes et al. 2005). This can be a relatively straightforward affair in comparison to identifying, measuring, and vetting a traditional instrument, as well as does not require the strong theoretical assumptions of a structural model, for example.

Guideline 4: Seek balance in methodological rigor and managerial relevance

Reibstein et al. (2009) recommend that a researcher "begin with an important topic and bring the best combinations of methodology, data, and theory" (pp. 1–2). The researcher always faces a task of weighing trade-offs for appropriate context, scope, operationalization, and methodology when designing their study. There exists both a multitude of potential causes of endogeneity, as well as a multitude of possible approaches to addressing it. Extant literature and good practice recommends that the researcher examine and thoroughly understand the identifying assumptions of competing methodologies to ascertain the most appropriate set for their theoretical research setting rather than try all feasible options and report the most favorable findings (Germann et al. 2015). For example, if the researcher is interested in purely predictive research for the purposes of forecasting, there is little reason to address endogeneity beyond including important explanatory variables that improve predictive performance (Ebbes et al. 2011). This is because the statistical correction of endogeneity results in less precise estimates and moves a linear regression away from the best linear predictor obtained from OLS. Alternatively, presentation of competing models and methodological choices can make the case for models that do not statistically address endogeneity if post "correction" the results show little meaningful difference. Comparison of this type should show that endogeneity-corrected models demonstrate estimates of magnitude and direction that align with that of the theoretical justification for their use.

Addressing potential endogeneity for the sake of methodological sophistication may be ill advised when simpler models with more robust data and fewer assumptions can provide more reliable estimates, particularly considering the ease with which the "rich can make themselves poor" though misapplication of the techniques discussed in this paper (Rossi 2014, p. 655). Fundamentally, there potentially is no optimal solution to addressing all possible endogeneity issues, only a set of approaches based on sound theoretical reasoning bounded by the feasibility of the research question itself.

Moving forward

Endogeneity still is a thorny issue for empirical marketing strategy research. In our experience as authors and reviewers we frequently see the "everything is endogenous" criticism as a simple reason offered to reject. From our perspective, the issue of endogeneity will most likely not disappear anytime soon. As such, we find it critical that researchers and reviewers engage in a productive discussion on potential issues and feasible solutions for any study at hand. From our view, these discussions should not solely focus on the flaws that non-experimental data typically has but on how existing approaches could be leveraged to address endogeneity issues as best as possible. We want to stress that from our perspective there is potentially no perfect solution for endogeneity when working with non-experimental data.

So what are the alternatives going forward? One possible solution could be to not use non-experimental data to understand firms' marketing strategies going forward. This seems an untenable approach to important managerial questions where academia can provide insights to managers. As we note above, field experiments are not always possible and even when possible come with their own set of issues (e.g., Johnson et al. 2017). A more moderate approach is what we are proposing. Based on our exposition, a researcher can determine which types of endogeneity issues might be a relevant concern in the study at hand. There are two benefits arising from this consideration. First, in modeling the data one or more of the techniques discussed above can be leveraged to mitigate the impact of endogeneity. This allows researchers to put their best effort in play when trying to gleam insights compared to a naïve model that does not try to address endogeneity. Second, the paper can already be written discussing these potential endogeneity concerns and thus starting a conversation with the review team about these concerns and the steps the authors have taken to address them. A more detailed discussion will allow the review team to focus on the arguments the authors are making versus simply noting that endogeneity concerns loom large, as so often is the case.

Furthermore, limited extant research attempts to understand the potential magnitude in effect sizes between corrected and non-corrected models in marketing research. Clearly, the origins of endogeneity in any particular model will be dependent upon the context of study and data collected, which may exhibit competing forces over effects. For example, while omitted variable bias may inflate the importance of a variable in absence of missing data, measurement error will attenuate effect sizes to zero, while simultaneity presents yet other issues of causal direction. However, it is an empirical question to assess the reported corrected and non-corrected differences in published studies. A future study could extend approaches such as Papies et al. (2017) through meta-analytic technics to better inform the managerial significance of methodological correction in more concrete terms. Such studies could provide meaningful evidence as to whether there is any significant tradeoff in methodological "purity" at the expense of managerial impact, as others have suggested (Lehmann et al. 2011; McAlister 2016; Houston 2016).

Our hope is that better understanding of sources of endogeneity and application of appropriate methodological correction techniques will lessen risks in initial study design as well as its subsequent review process, and mitigate surprises or undue discussions to the researcher. Ultimately, it is hard to imagine work based on non-experimental firm data that does not suffer at least some endogeneity concerns. As this manuscript details, all methods to address these concerns have certain issues and cost attached to them. Our four guidelines aim to help researchers confront the endogeneity issue with a strategy at hand and work through these guidelines to mitigate the endogeneity issues as much as possible. We hope that researchers and managers alike have improved their understanding of the endogeneity issue and potential cures to that important issue after reading our article.

References

Abhishek, V., Hosanagar, K., & Fader, P. S. (2015). Aggregation bias in sponsored search data: the curse and the cure. *Marketing Science, 34*(1), 59–77.

Ailawadi, K. L., Pauwels, K., & Steenkamp, J.-B. E. M. (2008). Private-label use and store loyalty. *Journal of Marketing, 72*(6), 19–30.

Anderson, E. T., & Simester, D. I. (2004). Long-run effects of promotion depth on new versus established customers: three field studies. *Marketing Science, 23*(1), 4–20.

Andrews, R. L., & Ebbes, P. (2014). Properties of instrumental variables estimation in logit-based demand models: finite sample results. *Journal of Modelling in Management, 9*(3), 261–289.

Andrews, R. L., Ainslie, A., & Currim, I. S. (2002). An empirical comparison of logit choice models with discrete vs. continuous representations of heterogeneity. *Journal of Marketing Research, 39*(4), 479–487.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of casual effects using instrumental variables. *Journal of the American Statistical Association, 91*(434), 444–455.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science, 57*(8), 1485–1509.

Ataman, M. B., Van Heerde, H. J., & Mela, C. F. (2010). The long-term effect of marketing strategy on brand sales. *Journal of Marketing Research, 47*(5), 866–882.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399–424.

Bagozzi, R. P. (1980). Performance and satisfaction in an industrial sales force: an examination of their antecedents and simultaneity. *Journal of Marketing, 44*(2), 65–77.

Balakrishna, N., & Lai, C. D. (2009), Concepts of stochastic dependence. In *Continuous bivariate distributions* (pp. 105–140) Springer, New York.

Ballings, M., McCullough, H., & Bharadwaj, N. (2018). Cause marketing and customer Profitabilitys. *Journal of the Academy of Marketing Science, 46*(2), 234–251.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics, 25*(2), 242–262.

Bronnenberg, B. J., & Sismeiro, C. (2002). Using multimarket data to predict performance in markets for which no or poor data exist. *Journal of Marketing Research, 39*(1), 1–17.

Calantone, R. J., Schmidt, J. B., & Michael Song, X. (1996). Controllable factors of new product success: a cross-national comparison. *Marketing Science, 15*(4), 341–358.

Chintagunta, P., Dubé, J.-P., & Singh, V. (2003). Balancing profitability and customer welfare in a supermarket chain. *Quantitative Marketing and Economics, 1*(1), 111–147.

Chintagunta, P., Kadiyali, V., & Vilcassim, N. J. (2004). Structural models of competition: A marketing strategy perspective. In C. Moorman & D. Lehmann (Eds.), *Assessing marketing strategy performance*. Cambridge: Marketing Science Institute.

Chintagunta, P., Erdem, T., Rossi, P. E., & Wedel, M. (2006). Structural modeling in marketing: review and assessment. *Marketing Science, 25*(6), 604–616.

Clougherty, J. A., Duso, T., & Muck, J. (2016). Correcting for self-selection based endogeneity in management research: review, recommendations and simulations. *Organizational Research Methods, 19*(2), 286–347.

Danaher, P. J., & Smith, M. S. (2011). Modeling multivariate distributions using copulas: applications in marketing. *Marketing Science, 30*(1), 4–21.

de Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device switching in online purchasing: examining the strategic contingencies. *Journal of Marketing, 82*(5), 1–19.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effects on sales. *Marketing Science, 14*(1), 1–21.

Dinner, I. M., van Heerde, H. J., & Neslin, S. A. (2014). Driving online and offline sales: the cross-channel effects of traditional, online display, and paid search advertising. *Journal of Marketing Research, 51*(5), 527–545.

Dubé, J.-P., Chintagunta, P., Petrin, A., Bronnenberg, B., Ron, G., Seetharaman, P. B., Sudhir, K., Thomadsen, R., & Zhao, Y. (2002). Structural applications of the discrete choice model. *Marketing Letters, 13*(3), 207–220.

Ebbes, P., Wedel, M., Steerneman, T. G. M., & Bockenholt, U. (2005). New evidence for the effect of education on income: solving endogeneity with latent instrumental variables. *Quantitative Marketing and Economics, 3*(4), 365–392.

Ebbes, P., Papies, D., & Van Heerde, H. J. (2011). The sense and non-sense of holdout sample validation in the presence of endogeneity. *Marketing Science, 30*(6), 1115–1122.

Ebbes, P., Papies, D., & van Heerde, H. J. (2016). Dealing with Endogeneity: A Nontechnical Guide for Marketing Researchers. C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research*, Springer International Publishing AG.

Elberse, A., & Eliashberg, J. (2003). Demand and supply dynamics for sequentially released products in international markets: the case of motion pictures. *Marketing Science, 22*(3), 329–354.

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science, 15*(1), 1–20.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Gatignon, H., & Xuereb, J.-M. (1997). Strategic orientation of the firm and new product performance. *Journal of Marketing Research, 34*(1), 77–90.

George, M., Kumar, V., & Grewal, D. (2013). Maximizing profits for a multi-category catalog retailer. *Journal of Retailing, 89*(4), 374–396.

Germann, F., Ebbes, P., & Grewal, R. (2015). The chief marketing officer matters! *Journal of Marketing, 79*(3), 1–22.

Godes, D., & Mayzlin, D. (2009). Firm-created word-of-mouth communication: evidence from a field test. *Marketing Science, 28*(4), 721–739.

Grewal, R., Cote, J. A., & Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: implications for theory testing. *Marketing Science, 23*(4), 519–529.

Grewal, R., Kumar, A., Mallapragada, G., & Saini, A. (2013). Marketing channels in foreign markets: control mechanisms and the moderating role of multinational Corporation Headquarters–subsidiary relationship. *Journal of Marketing Research, 50*(3), 378–398.

Grewal, D., Puccinelli, N. M., & Monroe, K. B. (2018). Meta-analysis: error cancels and truth accrues. *Journal of the Academy of Marketing Science, 46*(1), 9–30.

Guo, S., & Fraser, M. W. (2010). *Propensity score analysis: Statistical methods and applications*. Thousand Oaks: Sage Publications.

Hahn, J., & Hausman, J. (2002). A new specification test for the validity of instrumental variables. *Econometrica, 70*, 163–189.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica, 50*(4), 1029–1054.

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic Literature, 42*(4), 1009–1055.

Hausman, J. (1978). Specification tests for econometrics. *Econometrica, 46*, 1251–1271.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153–161.

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: conceptual foundations. *Journal of Marketing, 60*(3), 50–68.

Houston, M. B. (2016). Is 'strategy' a dirty word? *Journal of the Academy of Marketing Science, 44*(5), 557–561.

Jaworski, B. J. (2011). On managerial relevance. *Journal of Marketing, 75*(4), 211–224.

Johnson, G. A., Lewis, R. A., & Nubbemeyer, E. I. (2017). Ghost ads: improving the economics of measuring online ad effectiveness. *Journal of Marketing Research, 54*(6), 867–884.

Kadiyali, V., Sudhir, K., & Rao, V. R. (2000). Structural analysis of competitive behavior: new empirical industrial organization methods in marketing. *International Journal of Research in Marketing, 18*(1–2), 161–186.

Kennedy, P. (2008). *A guide to modern econometrics, vol* (2nd ed.). Oxford, UK: Blackwell.

Kleibergen, F., & Zivot, E. (2003). Bayesian and classical approaches to instrumental variable regression. *Journal of Econometrics, 114*(1), 29–72.

Kuhfeld, W. F., Tobias, R. D., & Garratt, M. (1994). Efficient experimental design with marketing research applications. *Journal of Marketing Research, 31*(4), 545–557.

Kuksov, D., & Villas-Boas, J. M. (2008). Endogeneity and individual consumer choice. *Journal of Marketing Research, 45*(6), 702–714.

Kumar, V., Zhang, X., & Luo, A. (2014). Modeling customer opt-in and opt-out in a permission-based marketing context. *Journal of Marketing Research, 51*(4), 403–419.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: the effects of firm generated content in social media on customer behavior. *Journal of Marketing, 80*(1), 7–25.

Lee, J.-Y., Sridhar, S., Henderson, C. M., & Palmatier, R. W. (2014). Effect of customer-centric structure on long-term financial performance. *Marketing Science, 34*(2), 250–268.

Leenheer, J., van Heerde, H. J., Bijmolt, T., & Smidt, A. (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self selecting members. *International Journal of Research in Marketing, 24*(1), 31–47.

Lehmann, D. R., McAlister, L., & Staelin, R. (2011). Sophistication in research in marketing. *Journal of Marketing, 75*(4), 155–165.

Leuven, E., & Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. *Statistical Software Components* S432001, Boston College Department of Economics, revised 01 Feb 2018.

Luan, Y. J., & Sudhir, K. (2010). Forecasting marketing-mix responsiveness for new products. *Journal of Marketing Research, 47*(3), 444–457.

Lucas, R. (1976). Econometric policy evaluation: A critique. *The Phillips curve and labor markets*. In Brunner, K.; Meltzer, A, Carnegie-Rochester Conference Series on Public Policy, New York: American Elsevier, pp. 19–46.

Mallapragada, G., Grewal, R., Mehta, R., & Dharwadkar, R. (2015). Virtual Interorganizational relationships in business-to-business electronic markets: heterogeneity in the effects of organizational interdependence on relational outcomes. *Journal of the Academy of Marketing Science, 43*(5), 610–628.

McAlister, L. (2016). Rigor versus method imperialism. *Journal of the Academy of Marketing Science, 44*(5), 565–567.

Naik, P. A., & Tsai, C.-L. (2000). Controlling measurement errors in models of advertising competition. *Journal of Marketing Research, 37*(1), 113–124.

Nelsen, R. B. (2006). An introduction to copulas. *Springer series in statistics*. New York: Springer.

Newey, W. K., & McFadden, D. (1994). Large sample estimation and hypothesis testing. *Handbook of Econometrics, 4*(1), 2111–2245.

Novak, S., & Stern, S. (2009). Complementarity among vertical integration decisions: evidence from automobile product development. *Management Science, 55*(2), 311–332.

Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: purpose, process, and structure. *Journal of the Academy of Marketing Science, 46*(1), 1–5.

Papies, D., Ebbes, P., & Van Heerde, H. J. (2017). Addressing endogeneity in marketing models. In P. Leeflang, J. Wieringa, T. Bijmolt, & K. Pauwels (Eds.), *Advanced methods for modeling markets. International series in quantitative marketing*. Cham: Springer.

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586.

Petrin, A., & Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research, 47*(1), 3–13.

Reibstein, D. J., Day, G., & Wind, J. (2009). Guest editorial: is marketing academia losing its way? *Journal of Marketing, 73*(4), 1–3.

Reiss, P. C., & Wolak, F. A. (2007). Structural econometric modeling: rationales and examples from industrial organization. *Handbook of Econometrics, 6*(1), 4277–4415.

Rinallo, D., & Basuroy, S. (2009). Does advertising spending influence media coverage of the advertiser? *Journal of Marketing, 73*(6), 33–46.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Rossi, P. E. (2014). Even the rich can make themselves poor: a critical examination of IV methods in marketing applications. *Marketing Science, 33*(5), 655–672.

Rutz, O. J., & Trusov, M. (2011). Zooming in on paid search ads—a consumer-level model calibrated on aggregated data. *Marketing Science, 30*(5), 789–800.

Rutz, O. J., Bucklin, R. E., & Sonnier, G. P. (2012). A latent instrumental variables approach to modeling keyword conversion in paid search advertising. *Journal of Marketing Research, 49*(3), 306–319.

Sande, J. B., & Ghosh, M. (2018). Endogeneity in survey research. *International Journal of Research in Marketing, 35*(2), 185–204.

Sanderson, E., & Windmeijer, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics, 190*(2), 212–221.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica, 26*(3), 393–415.

Sen, S., Bhattacharya, C. B., & Korschun, D. (2006). The role of corporate social responsibility in strengthening multiple stakeholder relationships: a field experiment. *Journal of the Academy of Marketing Science, 34*(2), 158–177.

Sonnier, G. P., McAlister, L., & Rutz, O. J. (2011). A dynamic model of the effect of online communications on firm sales. *Marketing Science, 30*(4), 702–716.

Sorescu, A., Warren, N. L., & Ertekin, L. (2017). Event study methodology in the marketing literature: an overview. *Journal of the Academy of Marketing Science, 45*(2), 186–207.

Srinivasan, R., Sridhar, S., Narayanan, S., & Sihi, D. (2013). Effects of opening and closing stores on chain retailer performance. *Journal of Retailing, 89*(2), 126–139.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics, 20*(4), 518–529.

Sun, B. (2005). Promotion effect on endogenous Consumption0. *Marketing Science, 24*(3), 430–443.

Van Heerde, H. J., Gijsenberg, M. J., Dekimpe, M. G., & Steenkamp, J.-B. E. M. (2013). Price and advertising effectiveness over the business cycle. *Journal of Marketing Research, 50*(2), 177–193.

Varadarajan, R. (2010). Strategic marketing and marketing strategy: conceptual domain, definition, fundamental issues and foundational premises. *Journal of the Academy of Marketing Science, 38*(2), 119–140.

Villas-Boas, J. M., & Winer, R. S. (1999). Endogeneity in brand choice models. *Management Science, 45*(10), 1324–1338.

Wedel, M., Kamakura, W., Arora, N., Essec, A. B., Chiang, J., Elrod, T., Johnson, R., Lenk, P., Nesling, S., & Poulsen, C. S. (1999). Discrete and continuous representations of unobserved heterogeneity in choice modeling. *Marketing Letters, 10*(3), 219–232.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge: MIT Press.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Nelson Education.

Zhang, J., Wedel, M., & Pieters, R. (2009). Sales effects of attention to feature advertisements: a Bayesian mediation analysis. *Journal of Marketing Research, 46*(5), 669–681.

Zhang, X., Kumar, V., & Cosguner, K. (2017). Dynamically managing a profitable email marketing program. *Journal of Marketing Research, 54*(6), 851–866.