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Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data

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A R T I C L E I N F O

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A B S T R A C T

Endogeneity bias can lead to inconsistent estimates and incorrect inferences, which may provide misleading conclusions and inappropriate theoretical interpretations. Sometimes, such bias can even lead to coefficients having the wrong sign. Although this is a long-standing issue, it is now emerging in marking and management science, with high-ranked journals increasingly exploring the issue. In this paper, we methodologically demonstrate how to detect and deal with endogeneity issues in panel data. For illustration purposes, we used a dataset consisting of observations over a 15-year period (i.e., 2002 to 2016) from 101 UK listed companies and examined the direct effect of R&D expenditures, corporate governance, and firms' characteristics on performance. Due to endogeneity bias, the result of our analyses indicates significant differences in findings reported under the ordinary least square (OLS) approach, fixed effects and the generalized method of moments (GMM) estimations. We also provide generic STATA commands that can be utilized by marketing researchers in implementing a GMM model that better controls for the three sources of endogeneity, namely, unobserved heterogeneity, simultaneity and dynamic endogeneity.

1. Introduction

Endogeneity in regression models refers to the condition in which an explanatory (endogenous, e.g., research and development expenditures) variable correlates with the error term, or if two error terms correlate when dealing with structural equation modelling. Endogeneity bias can therefore cause inconsistent estimates (i.e., not tend to be the true value as sample size increases), which potentially leads to wrong inferences, misleading conclusions and incorrect theoretical interpretations. Ketokivi and McIntosh (2017) even stated that researchers might not get the correct sign of coefficients in the presence of endogeneity bias. Research suggests approximately 90% of papers published in premier journals have not adequately addressed endogeneity bias (e.g., Antonakis, Bendahan, Jacquart, & Lalive, 2010; Hamilton & Nickerson, 2003). Based on a study of over 100 articles in top journals, it is claimed that "*researchers fail to address at least 66% and up to 90% of design and estimation conditions that make causal claims invalid*" (Antonakis et al., 2010, p. 1086).

Despite recent methodological advances and the relevant literature in econometrics/psychology, other social science disciplines (e.g., marketing, operations management, international business and supply chain management) have largely produced inconsistent estimates due to not addressing endogeneity biases. However, marketing (e.g., *Journal of Marketing, Journal of Marketing Research,* and more recently *Industrial Marketing Management*) and operations management (e.g., *Journal of Operations Management*) journals have started to take it more seriously, and asked authors to fully address endogeneity in their studies (e.g. Ketokivi & McIntosh, 2017; Reeb, Sakakibara, & Mahmood, 2012; Zaefarian, Kadile, Henneberg, & Leischnig, 2017). Researchers are responding to this call; for example, the *Industrial Marketing Management* journal has seen an increase number of authors addressing endogeneity bias in their studies published in 2017 (a total of 6 papers to be exact) compared to that of the previous year (only 1 paper). The reviewers associated with these journals have also played their part in directing researchers to address such methodological complications. Nonetheless, many researchers in management disciplines are not yet fully aware of endogeneity, its sources, and relevant remedies (Antonakis, Bendahan, & Lalive, 2014; Guide & Ketokivi, 2015; Zaefarian et al., 2017).

Importantly, endogeneity bias can have different origins, and different methods exist to address them. For example, the dynamic generalized method of moments model (GMM) is used to address panel data (i.e., dynamic endogeneity bias) and two-stage least squares

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(2SLS)/three-stage least squares (3SLS) are often used for survey data. Some researchers have recently provided reviews to understand the key endogeneity concepts and relevant techniques (e.g., see Zaefarian et al., 2017). However, a step-by-step procedure on how to execute these techniques for a particular research problem is still missing. We therefore provide a succinct overview of the key endogeneity sources and solutions, and comprehensively demonstrate the GMM method using a case study of a panel dataset consisting of 15 years of observations. Specifically, this study explores how the dynamic nature of investment in R&D expenditures together with corporate governance affect firm performance. To better illustrate how endogeneity bias may cause incorrect estimates, we examine our proposed model using three different approaches, namely, ordinary least square (OLS), fixed effects, and the generalized method of moments (GMM). Practically, our main aim and contribution is to provide a comprehensive procedure for researchers to produce consistent estimates and to draw valid inferences when dealing with panel data.

In addition, panel data is used far less frequently in business-to-business than in the business-to-consumer marketing domain, and this article could provide a starting point as to how industrial marketing and management researchers can utilize such datasets to provide insights for business practitioners. For instance, the research and development expenditure and its relationship to firm financial performance in industrial marketing can be explored by using panel datasets that are available from different databases (e.g., DataStream), unfortunately business and management researchers are often unaware of such resources).

2. Sources of endogeneity

The error term in endogeneity bias is unobservable, so there is no direct way to statistically test that an endogenous variable is correlated with the error term. Also, exogenous variables are probably never exogenous precisely (Ketokivi & McIntosh, 2017). It is therefore almost impossible to statistically ensure that an endogeneity problem can be completely resolved (Roberts & Whited, 2012). That is why such dilemmas do not ask for solutions, they require better choices (Ketokivi & McIntosh, 2017). For choices, researchers need to understand the sources of the problem and then take reasonable actions to reduce the negative impact in order to deal with endogeneity effectively. As there are no direct tests for endogeneity, the choices of indirect tests and precautionary measures can help to guide relevant insights and conclusions (Ketokivi & McIntosh, 2017). Endogeneity encompasses common-method variance, measurement errors, omitted variables/selections and simultaneity. It is important to address them theoretically (e.g., extensively reviewing literature and providing comprehensive research designs that could help to apply appropriate statistical tools) as well as empirically (e.g. using statistical techniques to ensure that data is rigorously investigated) (Antonakis et al., 2010; Ketokivi & McIntosh, 2017).

2.1. Common-method variance and its remedies

Common-method variance (CMV) is related to measurement methods. CMV is problematic due to its interlinks with the sources of measurement errors, These sources can come from common-rater effects (e.g., only collecting information from similar respondents), common measurement content (e.g., time, location and a single-medium used to collect data), common-item context or item characteristics (e.g., wording, length and clarity), scale types, respondents, response formats and the general content (Malhotra, Kim, & Patil, 2006; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Research suggests that the difference between the amounts of variance accounted is 24% when CMV is controlled (i.e., 35%) versus when it is not controlled (i.e., 11%). Thus, CMV can have a substantial effect on the relationships between measures or constructs (Podsakoff et al., 2003).

A series of steps can be taken to minimize the CMV bias. Theoretically, one can use research to develop a systematic questionnaire and measures (items) to form the constructs, which can be further refined statistically using exploratory factor analysis and reliability measures. It is good practice to avoid unfamiliar words, double-barrelled questions and technical words and to keep items simple, specific and concise. The items could be further grouped with different construct items (i.e., not in conceptual dimensions) (Tourangeau, Rips, & Rasinski, 2000). Some researchers also suggest to avoid adding (many) negatively-worded items because of a lack of confidence in respondents' ability to fully understand them, as highlighted by Podsakoff et al. (2003). Researchers often have to delete such items because their loadings are not strong enough to meet the minimum criterion. In addition, respondents should be informed of the anonymity of the survey - individuals and companies should not be identified and only aggregate data need to be used. Moreover, to avoid a single-informant bias, data could be collected from multiple informants. For example, a survey data collection may involve multiple management positions such as chief executive officers, managing directors, project managers, marketing managers, senior operations managers and team leaders (e.g., Akhtar, Tse, Khan, & Rao-Nicholson, 2016).

In order to test for CMV, researchers commonly use Harman's one-factor test (Malhotra et al., 2006; Podsakoff et al., 2003). In this method, the analysis produced from multiple factors (based on eigenvalues > 1 and scree plot observations) with reasonable variances is compared to a single factor solution or other combinations. However, this test is insensitive, and as such it is insufficient test to rule out the potential existence of common method bias (Podsakoff et al., 2003). Although all statistical approaches to control for CMV bias have their particular advantages and disadvantages (Malhotra et al., 2006; Podsakoff et al., 2003), it is also useful to apply the marker variable technique (e.g., the number of languages that respondents speak, as a marker variable) proposed by Lindell and Whitney (2001), which is a good alternative to assess the CMV bias. Additionally, the latent factor approach can be used for assessing CMV (see Malhotra et al., 2006). It is a good practice to use these mentioned multiple remedies to minimize possible concerns. This leads to employ different methods and one can follow a rigorous statistical procedure by using these techniques to deal with CMV.

2.2. Measurement errors

Measurement error is a common problem in marketing, management, business and other social science research. This is because the constructs of interest cannot be measured perfectly, as researchers can do in natural sciences. Consequently, the estimates are inconsistent and the error affects other variables involved (Antonakis et al., 2010, 2014; DeShon, 1998).

Although structural equation modelling analysis (e.g., maximum likelihood estimate) does correct for the biasing effects of measurement errors (Frone, Russell, & Cooper, 1994) or correct for the small amount of measurement errors (DeShon, 1998), researchers still need to control for measurement errors when they use a single indicator approach, that is parcelling using multi-item scales (DeShon, 1998). For example, if researchers use parcelling (averaging the relevant items) for environmental and financial (performance) constructs, they should be corrected for the random measurement error by constraining the relevant random error variance equal to the product of the variance multiply by one minus the reliability. The relevant loadings (i.e., SD ∗ square-root of alpha) for the parcels are also fixed (Antonakis et al., 2014; Bollen, 1989; DeShon, 1998). By controlling for the errors, besides minor changes in significance levels, researchers can find that the difference

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