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Version: Accepted Version

Article:
Ullah, S, Zaefarian, G and Ullah, F (2021) How to use instrumental variables in addressing endogeneity? A step-by-step procedure for non-specialists. Industrial Marketing Management, 96. A1-A6. ISSN: 0019-8501

https://doi.org/10.1016/j.indmarman.2020.03.006

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How to use instrumental variables in addressing endogeneity?
A step-by-step procedure for non-specialists

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Abstract

Endogeneity issues in empirical research have received increasing academic attention. Tackling endogeneity problems effectively and using the appropriate estimation techniques are important quality benchmarks in the publication process of many academic journals. In this paper, we discuss the use of instrumental variables (IVs) in business and marketing research, with a particular focus on its implementation in STATA. We discuss several pre- and postestimation tests that researchers can use to implement various versions of IVs in STATA, including two-stage least squares regression, limited information maximum likelihood estimation, and generalized method of moments.

Keywords: Instrumental variables, Endogeneity, Two-stage least squares, Limited information maximum likelihood, Generalized method of moments

1. Introduction

This paper builds on a series of methodological articles recently published in marketing, management, and accounting research related to the use of instrumental variables (IVs) (e.g., Baum, Schaffer, & Stillman; Bascle, 2008; Larcker & Rusticus, 2010; Lu et al., 2018; Papies et al., 2017; Ullah, Zaefarian, & Akhtar, 2018; Zaefarian et al., 2017). These studies provide theoretical and empirical demonstrations of how to effectively deal with endogeneity. We contribute to the methodological discourse on the use of IVs by demonstrating step-by-step procedures for implementing various versions of IVs in STATA, including two-stage least squares (2SLS) regression, limited information maximum likelihood (LIML) estimation, and generalized method of moments (GMM). We also discuss a series of preliminary tests (pre-tests) and postestimation tests that researchers can use when implementing and testing the validity of these IV-based estimation techniques. Our intention is to provide a step by step guideline to a not necessarily expert audience on how to use instrumental variables in addressing endogeneity.

Economics researchers generally provide a detailed and theoretically driven explanation for their choice of econometric estimation. However, few articles in marketing research report step-by-step procedures for detecting and dealing with endogeneity issues in cross-sectional and panel data. Addressing endogeneity issues is now an editorial concern in many elite journals (Lu et al., 2018). *"Most rigorous academic journals require, more or less as part of their editorial policy, that endogeneity must be addressed somehow"* (Ketokivi & Mclntosh, 2017, p. 3). As clear evidence of this, many top-tier academic journals (e.g., *Industrial Marketing Management*, *British Journal of Management*, *European Management Review*) have dedicated methodology sections. These methodology sections advance knowledge of the conceptual, theoretical, and empirical understandings of recent methodological approaches and developments in business and marketing research. Methodology papers help all stakeholders, including authors and reviewers, to correct for possible endogeneity concerns before submitting a manuscript to an academic outlet. In a recent editorial note, Guide and Ketokivi (2015) redefine the methodological criteria for the *Journal of Operations Management*, acknowledging that researchers do consider endogeneity seriously, particularly when such quality thresholds are clearly reemphasized by the editorial team. They note that of the 1,529

published articles in *Journal of Operations Management*, the percentage of articles that explicitly tackle endogeneity issues in operations management research increased from 5.4% before the publication of the editorial to 8.6% after its publication. In *Industrial Marketing Management* (IMM) journal, the endogeneity issue as stated by Zaefarian et al., (2017, p 40) was "… *a blind spot that has not been sufficiently addressed in research published in IMM*". Zaefarian et al., (2017) sensitized IMM researchers to the topic of endogeneity, following which, the *Industrial Marketing Management* journal has witnessed a sustainable growth in the number of published papers that have addressed endogeneity[1]. This indicates that methodological guidance and clarity from top management journals can enhance the validity and generalizability of published academic outputs.

We organize the rest of the paper as follows: Section 2 defines endogeneity and discusses its implications in academic research. Section 3 briefly explains the sources of endogeneity. Section 4 defines IVs. Section 5 considers how to identify the appropriate instrument. Section 6 suggests step-by-step procedures for implementing various versions of IVs in STATA. Section 7 discusses popular postestimations tests for IV-based estimations. Section 8 concludes the paper.

2. What is endogeneity and why it is a cause of concern?

Endogeneity in an econometric model occurs when an explanatory (independent) variable is correlated with the residuals (also known as the "error term," or "disturbance term") (Lu et al., 2018). Econometric experts and editors of leading academic journals believe that endogeneity is one of the "blind spots" that can lead to the rejection of academic papers in various stages of review (Guide & Ketokivi, 2015). In equation 1, we present a standard ordinary least squares (OLS) regression and demonstrate how endogeneity may arise in a implementing a standard OLS model:

$$Y_i = \alpha + \beta x_i + \varepsilon_i \quad (1)$$

[1] In 2017, 5 papers published in IMM have addressed the issue of endogeneity. This number has since increased to 13 and then to 25 in 2018 and 2019 respectively.

In this model, Y_i is the dependent variable, α is the constant term, β denotes the coefficients, x_i represents explanatory variable(s), and ε_i is the disturbance term (residuals). If all the assumptions of OLS hold and the error term/random disturbance (noise) in the relationship between the explanatory variables and the dependent variable is similar across all values of the explanatory variables, then OLS is the best estimator (Bascle, 2008). Simply stated, if an error term in an econometric model is constant, then "errors" are homoskedastic. Homoskedasticity is an important assumption of OLS. Under these circumstances, standard OLS will generate unbiased estimates (Wooldridge, 2006). A crucial assumption of OLS is that the error term is uncorrelated with the explanatory variable. The correlation between error term and explanatory variable, however, violates this fundamental assumption of OLS and subsequently leads to biased estimates. Without controlling for endogeneity with appropriate econometric techniques, researchers may establish "spurious correlations" between explanatory variables and the dependent variable. In addition to reporting inaccurate estimates of the coefficients, failing to correct for endogeneity may result in misleading policy recommendations and ambiguous avenues for future research.

With the introduction of business databases and big data analytics, econometric techniques are increasingly being applied beyond the business discipline. For example, cross-sectional, times-series, and panel data estimations are also used by researchers in the medical sciences and public health. Inappropriate estimation could, therefore, have severe implications for the interpretation and generalizability of results. As methodological techniques evolve over time, publishing an academic article in a top-tier journal with simple OLS regression is a challenging task. Reviewers and editors are applying greater methodological scrutiny to ensure that the choices of econometric estimation techniques are theoretically grounded and that results are robust to alternative estimation techniques. In the following section, we provide a brief overview of key sources of endogeneity issues.

3. Primary sources of endogeneity

The literature highlights three common sources of endogeneity: errors in variables, omitted variable bias, and simultaneity (for more examples and details, see Wooldridge, 2002; Zaefarian et al., 2017). Below, we will go through each of these sources of endogeneity in more depth.

Errors in variables (often known as "measurement error") arise when a variable is imperfectly measured (Wooldridge, 2002). The following generic STATA command can be used for errors-in-variables regression.

eivreg depvar indepvars, r(variable, reliability) (2)

For example, for a dependent variable Y and explanatory variables X1, X2, and X3, where a variable (e.g., X3) is measured with reliabilities of 0.90, researchers needs to specify the STATA syntax as follows: r(X3, 0.90). The *reliab* option specifies the measurement reliability for each independent variable measured with error. The following specific STATA command can be applied in the above case:

eivreg Y X1 X2 X3, r(X3,0.90) (3)

When the degree of reliability for a variable is not mentioned in the command, it is assumed that the variable has a degree of reliability equivalent to 1. Thus, if the *r* option in not specified, all variables will have a degree of reliability equivalent to 1. In this case, the results will be the same as OLS regression.

The omission of key variables in an econometric model causes omitted variable bias (Wooldrige, 2002). If key explanatory variables are neglected in an analysis, their impact will be considerably noticed in the disturbance term and will cause endogeneity problems (Zaefarian et al., 2017). Omitted variable is expected to be correlated with one or more than one explanatory variables in a regression model. An important condition for an omitted variable is that it must also be correlated with the dependent variable.

Germann et al. (2015) provide a relevant and useful example of omitted variable bias. In their study on whether the presence of Chief Marketing Officer's (CMO's) affect the performance of firms, they argue

that one should not simply regress firm performance on the dummy variable indicating CMO presence. Indeed, performance of firms are driven by several other factors (variables), such as organizational cultures and advertisement expenditure (that are correlated with dependent variable), which may also influence CMO's presence (that are correlated with the explanatory variable). Information on advertising expenditures can be observed through publicly disclosed financial data, however it is quite challenging to observe organizational culture, If these variables are not included in the model and are not considered in the analysis, the expected variations caused by these variables will be observed in the error term of a regression model, and would cause endogeneity problems. The unavailability of data for an important explanatory variable could be one of the reasons for omitted variable bias, and the emergence of firm-specific business and financial databases (i.e., Bloomberg, etc) could somehow facilitate business researchers to overcome this issue and capture relevant and reasonable number of firm-specific characteristics in their econometric analysis. Using several control variables can also help in controlling for omitted variable bias.

Simultaneity bias arises when the causal relationship between one (or more) explanatory variable are co-determined and they affect each other simultaneously (Wooldridge, 2002, 2006). In the CMO presence—performance example (as mentioned above), it is likely that CMO presence (explanatory variable), and advertising expenditure (control variable) could be determined concurrently with firm-specific financial performance (dependent variable). For instance, a firm may choose its advertising expenditure intensity based on its current/future profitability and financial performance, and hence both advertising expenditure and financial performance variables may occur simultaneously.

Dynamic endogeneity occurs when past values of the dependent variable affect current values (outcomes). For example, when considering the impact of recent advertising expenditures on a firm's current financial performance, it is possible that recent advertising expenditures are partly (fully) driven by the previous year's financial performance. Lagged values of the dependent variable (in this case, financial performance) are often used to control for dynamic endogeneity issues in panel data (see Ullah, Akhtar, & Zaefarian, 2018).

The use of IVs is a common technique for addressing endogeneity problems (Bascle, 2008; Sargan, 1958). Although, it is challenging to find a 'relevant' and a 'strong' instrument (as discussed in the subsequent section), the inclusion of a 'bad instrument' can potentially worsen the performance of the chosen econometric model (Bettis et al., 2014). Within the social sciences discipline, multiple alternative approaches (IVs, GMM, 2SLS, 3SLS) have been widely used to tackle different types of endogeneity issues (Lu et al., 2018), however, owing to its strict underlying assumptions in tackling endogeneity, and, conditions relating to finding suitable IVs, the IV-based estimation is still widely popular for cross sectional, and panel datasets. IVs approach is useful in controlling for several sources of endogeneity arising from: reverse causality/ 'simultaneous equations' bias, selection bias, measurement errors, or the presence of unmeasured confounding effects (Stock, 2015). However, IVs are not magical medicines in handling endoegenity issues, and inappropriate use of IVs may create further problems in generating inconsistent coefficients, and interpretations. For instance, if one of the chosen instruments is endogenous then LIML, and 2SLS estimators would produce inconsistent results.

In the remainder of this paper, we examine the choice of IVs and implementations in STATA.

4. What is an IV?

IVs are variables that are uncorrelated with the error term (disturbance term) but are correlated with the endogenous explanatory variable(s), though they do not represent explanatory variables in the original regression model (Murray, 2006; cited in Zaefarian et al., 2017, p 41). The general economic intuition is that IV-based estimation decomposes observed variations in explanatory variables into two parts: an exogenous part and an endogenous part. Therefore, IVs segregate exogenous variation by employing additional regression, commonly known as "first-stage regression" (Papies et al., 2017, p. 586). The use of an additional variable is known as an IV. IV estimation is often used interchangeably with two-stage least squares (2SLS); however, IV-based estimation approaches may use other estimators, such as limited information maximum likelihood (LIML) estimation and generalized method of moments (GMM) (Semadeni, Withers, & Trevis, 2014).

The 2SLS approach is a commonly used IV estimation technique. The implementation of IV-based estimation involves considerable theoretical and empirical justification. For example, researchers need to confirm the presence of endogeneity through several statistical tests. In addition, endogenous variables need to be carefully assessed and interpreted in light of the extant literature/theory. Most important, researchers often employ "lagged values" without carefully considering the quality of such instruments. Rossi (2014) discourages the use of IV-based regression if only lagged values are considered "instruments," because this practice cannot be fully justified from an econometrics perspective. Papies et al. (2017, p. 586) argue that:

> "*if a researcher (or reviewer) has strong theory- or evidence-based arguments that there is a relevant correlation between one or more regressors and the model error term, then the most common method to estimate the parameters of interest is through IV estimation."*

In the next section, we explain what criteria researchers can use to check for a good instrument.

5. How to find a good instrument

Finding a valid instrument (a suitable IV)[2] is a challenge that many researchers face, and both the choice and strength of a valid IV play an important role in the implementation of an IV. The strict limitations on both strength and validity of instrumental variables have made them hard to find (Lu et al., 2018; Rossi, 2014). Moreover, the use of weak or "*invalid instruments can cause the estimates to differ even when there is no endogeneity bias*" (Rossi, 2014. p 671). Several scholars have argued that the choice and use of poor instrument variable can do more harm than good. Indeed poor instrument variables are not "cure", if any, they are more of a "disease" (Rossi, 2014; Semadeni, Withers, & Certo, 2014). As such there has been many attempts delineating how to find a good instrument. The overall conclusion of the literature is that researchers should always rely on theory, theory, and more theory.

[2] It is a major challenge for researchers to find a valid IV, which is strongly correlated with the endogenous variable but uncorrelated with the disturbance term in the second stage. In other words, it is also highly likely that as the instrument gets stronger, it also surprisingly correlates with the disturbance term in a similar way (Semadeni, Withers, & Trevis, 2014, p.1072).

As a general guideline, researchers can find instrument variables either outside their unite of analysis (e.g. within physical or institutional environment), outside the unit of analysis yet being affected by the unit of analysis (e.g. within organizational environment), or within unit of analysis (such as lagged variables). Whilst finding an instrument variable outside the unit of analysis increases the chance that the selected IV meets the exogeneity condition, it is less likely that such IV can meet the relevance condition. In contrast, finding an instrument variable within the unit of analysis while increases the likelihood of meeting relevance condition, is very unlikely to meet the exogenous condition – particularly in business marketing research.

Before implementing an IV in STATA, researchers need to confirm that the chosen instruments are (1) relevant[3] and (2) exogenous[4] (Keneddy, 2008). The term "instrument relevance" is often used in the former case, where researchers can test the relevance of a chosen instrument (strong vs. weak) to assess the impact of a relevant instrument on the results. A weak instrument is weakly correlated with the endogenous variable, and as a result, researchers will observe higher standard errors (Semadeni, Withers, & Trevis, 2014). More importantly, if there is no correlation between the instrument and the endogenous variable, the instrument (in this case, the chosen IV) is considered irrelevant (Bascle, 2008).

To check the instrument relevance assumption, several statistical tests can be implemented in STATA. The purpose of these additional checks is to compare how R^2 of the first-stage regression changes after additional instruments are included in the model. Technically, the subsequent changes in R^2 should be significantly higher (Papies et al., 2017, p. 593). The first-stage *F*-statistics proposed by Stock, Wright, and Yogo (2002) can be used to ascertain the relevance of an instrument. Higher *F*-statistics indicate that the chosen instruments can be considered in the 2SLS. Conversely, lower *F*-statistics indicate a weaker instrument (Semadeni, Withers, & Trevis, 2014). Users can apply the *ffirst* option with *ivreg2*[5] in STATA to obtain *F*-statistics in the first-stage regression (Bascle, 2008). Papies et al. (2017) suggest that researchers should report R^2 values for the first-stage regression (without IVs

[3] Relevant means the degree of correlation between the instrument and the endogenous variables.
[4] Exogenous refers to the extent to which the chosen instrument and the disturbance terms are uncorrelated.

[5] *Ivreg* implements IV regression, and *ivreg2* is an alternative command to STATA's official *ivregress*. *Ivreg2* can be installed in STATA using the following command: *ssc install ivrge2.*

and with IVs), as well as values for the "incremental" *F*-statistics. Instrument exogeneity/orthogonality implies that the instrument is uncorrelated with the disturbance term in the equation. This test of overidentifying restrictions can be used in STATA to check the exogeneity of the instruments. In the postestimation tests, we explain how the STATA command *estat overid* can be used to check the exogeneity of the instrument. We also explain how to interpret Sargan and Basmann tests to determine the exogeneity of the instrument.

6. IV implementation in STATA

In Table 1, we present several general STATA commands for implementing IV regressions, including some postestimation tests. The *ivregress* command can be used to implement various versions of IVs, including 2SLS, LIML, and GMM. The following generic STATA command can be used in implementing IV-2SLS:

ivregress 2sls dependent-variable list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables) (4)

[Insert Table 1 here]

The *ivregress*[6] command in STATA fits a single equation rather than using a system of multiple equations.[7] In the 2SLS STATA code, assume there is one endogenous variable (regressor) as identified in parentheses; we will need to find an additional variable (instrument) that is strongly correlated with this endogenous variable but uncorrelated with the error term. In addition, excluded exogenous variables should not directly affect the dependent variable. However, if they have an effect on the dependent variable, then they should be included as standard regressors in the econometric model.[8] As we discussed in the preceding section, researchers need to fully justify the choice of additional variables

[6] In the case of panel data, the *xtivreg* command can be used to fit panel data models in which one or more variables are endogenous on the right-hand side of the equation.
[7] For an example of first-stage and second-stage regression equations, see Zaefarian et al. (2017, p. 41).
[8] For further details, see *STATA Base Reference Manual* (2011), available at https://www.stata.com/manuals/r.pdf.

(instruments) using common intuition and prior empirical research and by applying the assumptions of a relevant economic theory. It is also recommended that once an IV-based regression model is implemented, researchers should carry out a series of robustness checks to test the sensitivity of the chosen instrument(s).

In the case of weak instruments and a "small sample," the LIML estimator can be more effective than 2SLS (Bascle, 2008; Papies et al., 2017). LIML can be implemented with the following generic STATA command:

ivregress liml dependent-variable list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables) (5)

LIML is essentially a linear combination of the OLS and 2SLS estimates. In section 7.2, we further explain the statistical tests that can be used to assess the explanatory power of the instrument (instrument relevance).

The following generic STATA command can be used in implementing GMM for serial auto correlation and heteroskedasticity:[9]

ivregress gmm dependent-variable list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables), wmatrix (robust) (6)

In the following section, we discuss several IV-based postestimation tests, including their interpretations with relevant STATA codes.

7. Postestimation tests in STATA

A series of postestimation tests can be used while implementing IV-based estimations. In Table 2, we summarize these postestimation tests and relevant STATA commands. Next, we discuss these tests individually.

[Insert Table 2 here]

7.1 Test of endogeneity (Durban and Wu-Hausman tests)

[9] In Section 7, we briefly explain the implications of serial autocorrelation and heteroskedasticity.

If the perceived endogenous variables turn out to be exogenous, then endogeneity is not a cause for concern, and standard OLS will be more efficient (Papies et al., 2017). The following STATA command can be used immediately after implementing the IV regression (ivregress) to check for possible endogeneity issues.

estat endogenous (7)

All the endogenous variables in equation 4 are tested because no particular variables are specified in this STATA command. This STATA command generates Durbin and Wu-Hausman tests (the null hypothesis states that variables are exogenous). Therefore, if these tests are statistically significant, it would indicate an endogeneity issue in the model. The following command can be implemented to test exogeneity of specific variables (e.g., Y1, Y2):

estat endogenous Y1 Y2 (8)

Endogeneity tests are subject to limitations. As Lu et al. (2018, p. 59) argue, *"the reliability of the endogeneity tests depends on the quality of the IVs."* In the following section, we discuss several tests that can be used to ascertain the explanatory power of an instrument.

7.2 Weak instrument tests

As we note in Section 5, the chosen IV must be highly correlated with the endogenous variables but should be uncorrelated with the disturbance term (error term). The weak instrument tests (Stock-Yogo test/*F*-statistics) are implemented in STATA to judge the explanatory power of the instruments. These tests assess the level of correlation between the additionally included IVs and the endogenous variables. In Section 5, we note that chosen instruments need to be relevant and exogenous. The following command is used to carry out a formal postestimation test after implementing the standard IV-based regression, as stated in equation 4:

estat firststage (9)

This command generates a series of test statistics, including first-stage *F*-statistics, which are often considered a "more robust and conservative test that should always be reported" (Bascle, 2008, p. 295).

The criteria and threshold for first-stage *F*-statistics is very simple. The null hypothesis states that the instruments are weak (for further details, see *STATA Base Reference Manual*, 2011). Instruments are likely to be strong (relevant) if the *F*-statistic is greater than 9.08 with three instruments and greater than 10.83 with five instruments (see Stock and Yogo, 2004, Table 1; cited in Bascle, 2008).

7.3 Tests of overidentifying restrictions

A model is "just-identified" when the number of instruments equals the number of endogenous variables, and a model is "overidentified" when the number of instruments is greater than the number of endogenous variables (Lu et al., 2017).[10] A test of the overidentifying restriction is conducted to assess the "exogeneity condition" of the instruments. Finding an instrument for multiple endogenous variables may not be very practical (Lu et al., 2017). Theoretically, the instruments must be uncorrelated with the disturbance term (i.e., the error term) (Papies et al., 2017). Tests of overidentifying restrictions/orthogonality condition also confirm whether the instrument or model is correctly specified (*STATA Base Reference Manual*, 2011, p. 836).

The following STATA command tests for exogeneity condition:

estat overid (10)

This test reports Sargan's and Basmann's χ^2 tests for 2SLS (without robust VCE) and Wooldridge's robust score if 2SLS is implemented with a robust VCE. In the case of GMM, this command reports a Hansen *J*-test, which allows for heteroskedasticity of errors (Papies et al., 2017, p. 595). In the case of the LIML estimator, the command reports an Anderson-Rubin likelihood ratio test and a Basmann *F*-test (*STATA Base Reference Manual*, 2011). The postestimation command can therefore be used after implementing various versions of IV-based regressions (2SLS, LIML, GMM). If Sargan's and Basmann's tests are significant, this implies that one or more of the instruments are not valid or that the equation (model) is incorrectly specified.

[10] See Lu et al. (2017, p. 57) for a list of statistical tests for *just-identified* models.

7.4 Test of heteroskedasticity for IV estimation

The issue of heteroskedasticity occurs in the error term. Heteroskedasticity implies that the variance of the error term is nonconstant (that it increases or decreases with changes in the variables) (Gujrati, 2004, p. 69). The issue of heteroskedasticity in particular is related to both cross-sectional and panel data (Bascle, 2008). The *ivhettest* command can be implemented in STATA after *regress ivreg* and *ivreg2*. The *ivhettest* command implements the Pagan-Hall test and other relevant heteroskedasticity tests after OLS and IV estimation.

7.5 Test for serial correlation (Arellano-Bond autocorrelation test)

According to Bascle (2008, p. 301), *"serially correlated errors mean that their effect is carried, at least in parts, across periods."* The Arellano-Bond test for autocorrelation (the STATA command *abar*) can be used for cross-section time-series data.[11] The *abar*[12] command can be implemented after various versions of regression in STATA, including *regress* (*ivreg, ivreg2*, *ivreg2*, *gmm2s*, *and ivregress 2sls*) in different variants (e.g., homoskedastic/plain, robust, and cluster variants) (Roodman, 2006). These pre- and postestimation tests provide an overview of when and how to apply these for various IV-based estimations, as well as how these tests can be interpreted carefully when choosing and implementing IVs.

8. Discussion and Conclusion

The concept of endogeneity is often viewed as a *"blind spot"* or a *"thorny issue"* in academic publishing. More recently, in the positivist research traditions, which rely heavily on sophisticated econometric techniques, tackling endogeneity with appropriate econometric estimation(s) is an important benchmark of quality research. Increasingly, both editors and reviewers have begun to

[11] The following Stata command is used to implement the Arellano-Bond test for no serial correlation when implementing a dynamic panel data two-step system GMM: *estat abond* (see Roodman, 2006).

scrutinize the choices and justifications for methodological approaches used in business research. Failure to correct for endogeneity may lead researchers to derive misleading conclusions due to spurious correlations between the chosen variables of interest. Many elite academic journals have dedicated methodology sections that enhance our understanding of methods and recent methodological developments in the discipline. Many economics journals have begun asking (or in some cases, insisting) that researchers share their research data (including raw or processed data files, software, codes, models, algorithms, protocols, methods, etc.). This will not only enhance the transparency and integrity of academic research but will also help other researchers learn from and replicate techniques for their own research. We argue that demonstrating step-by-step methodological procedures in empirical research can enhance the visibility of research methods for other researchers and can boost academic citations. Clear methodological approaches make it easier for other researchers to adapt and justify their chosen technique(s), thus making methodology papers more accessible and discoverable.

In this article, we discuss the economic intuition for applying IV-based estimation and its implementation procedures in STATA. Theoretically, as we discussed in the preceding section, IVs should be uncorrelated with the error term (disturbance term) but correlated with the endogenous variable. Popular IV-based estimations include 2SLS, LIML estimation, and GMM. We also argue that applying simple lagged values will not overcome the endogeneity problem. Before implementing IV-based estimations in STATA, researchers need to ensure that the chosen instrument is strong (relevant) and exogenous. To assess the relevance assumption, researchers can compare and observe changes in R^2 of the first-stage regression after incorporating additional instruments in the econometric model. First-stage *F*-statistics are also analyzed to ascertain the relevance of an instrument, and higher *F*-statistics suggest that instruments can be included in the 2SLS regression. Nevertheless, IVs should not appear out of the blue, and researchers need to fully explain and justify their choice of any additional instrument(s) by applying general intuition, using the assumptions of a relevant economic theory, and providing evidence from prior empirical research.

We also explain some reasons for using postestimation tests and its implementations in STATA to confirm the validity of the instrument/model. The Durbin and Wu-Hausman tests can be applied to test the endogeneity issues (though users also need to be aware of the limitations of these postestimation

tests). The weak instrument tests (Stock-Yogo test/*F*-statistics) are implemented in STATA to judge the explanatory power of the instruments. Furthermore, tests of overidentifying restrictions/orthogonality condition are applied to assess the "exogeneity condition" of the instruments and to confirm whether the instrument or model is correctly specified (*STATA Base Reference Manual*, 2011, p. 836). Similarly, the Arellano-Bond test for autocorrelation can be used to check for serial correlation.

In summary, we discuss generic STATA commands for IVs, and users need to carefully assess the suitability of various IV-based estimations for their own unique research settings. Discussing the limitations of an IV approach, Cameron and Trivedi (2005, p. 95) argue that it has been *"widely used in econometrics and rarely used elsewhere, is conceptually difficult and easily misused."* We believe that researchers who want to publish in *Industrial Marketing Management* and other elite journals will need to carefully tackle potential endogeneity problems whether using cross-sectional, time-series, panel, or survey data. We also believe that clear empirical demonstration and justification for methodological approaches will further enhance the quality of academic publications.

References

Bascle, G. (2008). Controlling for endogeneity with instrumental variables in strategic management research. *Strategic Organization*, *6(3),* 285-327.

Baum, C.F., Schaffer, M.E. and Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The STATA Journal*, *3(1)*, 1-31.

Bettis, R., Gambardella, A., Helfat, C. & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal*, *35*(7), pp.949-953.

Cameron, A.C. & Trivedi, P.K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press.

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

Guide Jr, V.D.R. & Ketokivi, M. (2015). Notes from the Editors: Redefining some methodological criteria for the journal. *Journal of Operations Management*, *37(1)*, v-viii.

Gujarati, D.N. (2004). *Basic Econometrics*. Tata McGraw-Hill Education.

Kennedy, P.(2008). *A Guide to Econometrics.* 2008. Malden, MA: Blackwell.

Ketokivi, M., & McIntosh, C. N. (2017). Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. *Journal of Operations Management*, 52, 1–14.

Larcker, D.F. & Rusticus, T.O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting and Economics*, *49(3),* 186-205.

Lu, G., Ding, X.D., Peng, D.X. & Chuang, H.H.C. (2018). Addressing endogeneity in operations management research: Recent developments, common problems, and directions for future research. *Journal of Operations Management,* 64, 53-64.

Papies, D., Ebbes, P. & Van Heerde, H.J. (2017). Addressing endogeneity in marketing models. In *Advanced Methods for Modelling Markets* (pp. 581-627). Springer, Cham.

Roodman, D. (2006). How to Do xtabond2: An Introduction to "Difference" and "System" GMM in STATA. Working Paper 103. Center for Global Development, Washington.

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.

Semadeni, M., Withers, M.C. & Trevis Certo, S. (2014). The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. *Strategic Management Journal*, *35(7),* 1070-1079.

STATA, S. (2011). *Base Reference Manual*. College Station, Texas.

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

Ullah, S., Akhtar, P. and Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management,* 71, 69-78.

Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data.* MIT press.

Wooldridge. (2006) *Introductory Econometrics: A Modern Approach,* 3rd edition, Mason, OH: Thomson South Westren.

Zaefarian, G., Kadile, V., Henneberg, S.C. & Leischnig, A. (2017). Endogeneity bias in marketing research: Problem, causes and remedies. *Industrial Marketing Management*, 65, pp.39-46

Table 1

Generic STATA Codes for IV implementation

Instrumental variables (2SLS) regression	ivregress 2sls dependent-variable list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables)
Instrumental variables LIML regression	ivregress liml *dependent-variable* list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables)
IV-GMM for serial auto correlation and heteroscedasticity	ivregress gmm dependent-variable list-of-included-exogenous-variables (endogenous regressors = excluded exogenous variables), wmatrix (robust)

Table 2

Postestimation tests for various IV-based estimations

Tests	STATA Codes
Test of endogeneity (Durban and Wu-Hausman tests)	estat endogenous
Testing exogeneity of multiple regressors (e.g., to test whether Y1 Y2 can be considered as exogenous)	estat endogenous Y1 Y2
Weak instrument tests (judging the explanatory power of the Instruments, Stock-Yogo test/F-Statistics)	estat firststage
Tests of overidentifying restrictions (testing the validity of the instruments/model, Sragan and Basmann tests)	estat overid
Test of heteroskedasticity for instrumental variables (IV) estimation	ivhettest
Test for serial correlation (Arellano-Bond autocorrelation test)	abar