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Endogeneity and Causal Attributions in Management Research: Some Reflections and Proposals *

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ABSTRACT

This article explores the pivotal role of causal identification in the domain of management research and its alignment with theory creation. It seeks to stimulate thought about how researchers can approach theories and their causal identification with a review of the canonical methods. The article first addresses the intricacies of identification and the principal methodologies that researchers have recently employed in their investigations. Subsequently, it delves into the inherent costs associated with identification, specifically the need for additional assumptions, and the potential constraints on generalizability. It also promotes a more thoroughly examination of the nature of endogeneity. Finally, it explores how the link between causal identification and theory legitimacy could generate superstitious trajectories.

Keywords: theory, causality, endogeneity, management research

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1. Introduction

Within broadly defined management research, there has been a growing and vigorous discourse regarding the significance of theory and its empirical validation (Shaw, 2017; Bettis et al., 2014). Numerous articles have begun to substantially enrich the management literature, focusing on the role of theory validation (Filatotchev et al., 2024; Oswick et al., 2011; Folger and Stein, 2017), generalization (Arora et al., 2016), the implications of causal identification costs, and the imperative need for replications (Ethiraj et al., 2016). This article embarks on this dynamic dialogue, with its primary objective being the raising of fundamental questions regarding the double feedback between empirical causality and theory (Agarwal and Hoetker, 2007; Durand et al., 2017). At the heart of most research lies the symbiotic relationship between theory, which inherently seeks to explain phenomena with logical connections, and empirics, which strives to typically validate theoretical constructs[1]. This prompts the management community to better consider the intricate interplay between theoretical constructs and empirical evidence in the context of their research efforts.

To tackle this matter, the article focuses in particular on the intricacies between causal identification and endogeneity, along with the principal methodologies that researchers have recently employed in their investigations. Subsequently, it delves into the inherent *costs* associated with identification, specifically, the need for additional assumptions and the potential constraints on generalizability. This section particularly emphasizes the tension between making precise causal attributions and the scope of generalizing theory applications once validated.

Then, the article underscores the significance of promoting a broader adoption of tests designed to scrutinize the issue of endogeneity within datasets, before proposing potential remedies. The central argument posits that endogeneity is typically not uniformly distributed across the sample, and that a thorough analysis of the magnitude and direction

[1]Needless to say, management research spans a spectrum from pure qualitative studies to canonical regression analyses (Bitektine, 2008). Our article focuses primarily on studies structured with an ex-ante theory, abducted hypotheses, and subsequent empirical validation tests (Heckman and Singer, 2017).

of biases, as well as its differential impact on distinct segments of the sample, can yield a more profound understanding of the theoretical mechanisms at play (Park and Gupta, 2012; Khalil and Yıldız, 2022).

To summarize, this article aims to explore the critical role of causal identification in management research and its connection to theory legitimacy. It emphasizes two potential drawbacks that may arise from biased interpretations of empirical causal identification. These biases could endow theories with unwarranted legitimacy, resulting in superstitious research trajectories (Levitt and March, 1988; Zollo, 2009; Filatotchev et al., 2024). In addition, the article underscores the importance of thoroughly investigating and not only mitigating endogeneity issues within a specific dataset. It emphasizes the need to highlight the inherent problematic aspects, specify the boundaries, and delineate the limitations of proposed solutions. This approach could foster a more conscious and dynamic epistemological debate within the field of management research (Durand and Vaara, 2009; Birkinshaw et al., 2014).

2. Endogeneity and causality

Causality is a fundamental concern in data analysis that pervades research in various domains, including data sources as diverse as secondary data, laboratory experiments, and vignette-based surveys. The pivotal question revolves around the researcher's ability to ascertain the extent to which empirical patterns observed in the data can transition from mere statistical correlations to establishing causal relationships (Wooldridge, 2010; Angrist and Pischke, 2009).

Empirical causality, in this context, denotes that a dependent variable, labeled Y, undergoes changes when a key covariate, labeled x, experiences random and independent variations, free from the influence of other variables within the system. The relationship should not be bidirectional, but unidirectional: From variable x to variable Y. Moreover, this primary covariate is assumed to be uncorrelated with the random noise produced by the estimation equation. The presence of a causal link usually serves as validation of some

theoretical constructs developed through mathematical or logical verbal mechanisms. The significance of causality extends beyond the validation of the theory, as it forms the foundation for the prescriptive and predictive power of a theory, offering explanations for real-world phenomena and guiding potential courses of action at different levels, such as, managers, entrepreneurs, and policy makers.

However, the concept of endogeneity introduces a complicating factor in which the covariate of interest becomes correlated with the error term, leading to a potential under-estimation or over-estimation in the relationship between Y and x. These issues can undermine the establishment of a causal relationship between the independent variable and the focal covariate. As a critical factor, endogeneity often arises from unobservable variables and measurement errors, which compromise the purity of the estimation process.

2.1. Common solutions

In research employing secondary data, several strategies are commonly employed to address endogeneity. These strategies include the use of exogenous shocks, randomization, matching techniques, and instrumental variables (IVs).

Exogenous shocks (Flammer, 2015; Conti, 2014) are based on unpredictable events that impact the strength of the relationship between Y and x, but this change is confined to a specific subset of observations. As a result, employing a difference-in-difference model can assist in obtaining a clearer estimation of the relationship under investigation.

Randomization (Bagues et al., 2017; Kuhn et al., 2011), on the other hand, occurs when the covariate of interest, x, undergoes random and independent variations due to the specific design of an event, such as the composition of a committee or the order of entry in a tournament. This approach mitigates endogeneity by ensuring that variations in x are not influenced by other system variables.

Matching techniques (Dickler et al., 2022; Eberhart et al., 2017), both synthetic and natural, aid in creating a control group where all other system variables remain statistically indistinguishable, while the primary covariate x is allowed to vary. This adjustment in the characteristics of the baseline dataset effectively reduces endogeneity.

IVs (Li et al., 2022; Wang et al., 2022) are covariates that induce changes in the core explanatory variable, x, without impacting Y. Consequently, IVs can be used to reduce the correlation between the error terms and x, helping to address endogeneity in the analysis.

In research using primary data, endogeneity could be largely avoided because of the experimental design of data collection. Experiments carried out in laboratories (Cappelen et al., 2019), field surveys (Harrison and List, 2004), or vignette-based surveys (Di Stefano and Gutierrez, 2019) mechanically introduce a randomization process in the respondents given different manipulation of variables.

2.2. *The costs of solutions*

Although the methods listed in the previous paragraph offer valuable tools to address endogeneity, researchers must be attuned to the specific assumptions and limitations introduced by each approach. Researchers may sometimes overlook these inherent costs, but it is imperative to transparently address how achieving identification might necessitate the abandonment of some broader assumptions. Thus, a clear and transparent consideration of these assumptions is essential to reduce any form of opacity of the empirical results, which could cause biased interpretations, especially in terms of generalization. This is because, to ensure causal identification, a certain level of complexity must be introduced into the econometric system.

Commencing with primary data, let us consider the assumptions required for generalization beyond experimental conditions. These encompass the expectation of unbiased behavior exhibited during the experiment, the assumption of effective and accurate comprehension of a text by the respondents, and the consistency of validated scales across different time points and subjects. In particular, in this context, the proliferation of a continuous stream of replication studies is of particular significance, fortifying the methodological foundation and improving the robustness of the findings (Ethiraj et al., 2016). Furthermore, robust meta-analyses that compile results from previously published studies without introducing new data are crucial to obtaining a complete understanding of a statistical phenomenon (Geyskens et al., 2009).

In the domain of secondary data analysis, the use of exogenous shocks and randomization techniques is again based on certain assumptions. These methods assume that only the focal covariate (x) is impacted by the shock, and no other system variables. Additionally, they presuppose that these shocks or randomization processes cannot be endogenously anticipated, designed, or tailored to suit specific objectives. Moreover, the estimation is often confined to a specific time window or particular event, which may limit the extent of generalization beyond these defined parameters.

Matching techniques introduce a set of assumptions that allow the modification of baseline control groups by either excluding certain observations or generating synthetic new control observations. Assuming that the assumptions are accurate, this method can be a useful way to reduce endogeneity. However, the selection or exclusion of matching variables is essential to ensure a correct interpretation of the results, which depend on the statistical distribution of these variables in the sample. Therefore, the results should be interpreted in the context of the particular baseline created with these techniques, and not on the whole sample.

The assumptions tied to IVs are complex and go beyond two fundamental considerations: i) the instrument's ability to effectively predict x, and ii) the requirement that, based on this prediction, the instrument should not demonstrate an independent association with the outcome variable Y. These assumptions transcend mere statistical considerations, as they are deeply entwined with the underlying theoretical constructs that underpin these relationships. Consequently, these assumptions introduce complexity, necessitating the incorporation of a new system of equations.

2.3. Assessing endogeneity

An often overlooked critical aspect is the examination of endogeneity issues within a specific sample before considering any potential solutions. Indeed, a prudent approach would entail a comprehensive understanding of the endogeneity problem before suggesting targeted solutions. This is mainly due to the need to consider at least three crucial factors when investigating endogeneity. These factors not only can help fine-tune potential solutions by better comprehending the root causes of endogeneity, but they

could also have the potential to inspire fresh theoretical insights stemming from the discoveries made.

These three factors are: i) the magnitude of bias; ii) the direction of bias; and iii) the identification of those sample observations mostly affected by this bias. Understanding the size of the bias and whether a researcher is over- or under-estimating a parameter can offer valuable feedback, not only regarding the confidence in the average results of regressions, but also for delving deeper into the underlying causes. Over- or under-estimation can be highly informative in shedding light on the nature of the biases at play, especially in terms of behavior and dynamics beyond the data.

The third point, although more subtle, is of significant importance. Typically, bias does not uniformly affect all observations of the sample. An illustrative example is an unobservable selection process that introduces bias only in specific subsamples. Applying a one-size-fits-all endogeneity solution to the entire sample, while mitigating bias, can discourage researchers from conducting in-depth analyses to understand why particular sub-sample of the sample generate over- or under-estimation.

Recently, some endogeneity tests have emerged that make use of non-normal or bunched control variables (Khalil and Yıldız, 2022; Park and Gupta, 2012). These approaches, although not necessarily providing solutions, operate under relatively mild assumptions. The key assumption here is that non-normality or bunching phenomena are indicative of unobservable endogeneity. The underlying rationale involves constructing tests that examine estimates when introducing a new simulated variable or changes in core estimates from both sides of a discontinuity. These tests can shed light on the three facets of inquiry mentioned earlier.

For instance, consider a scenario where a researcher exploits a bouncing variable in the controls to uncover biases in different sub-samples. This approach could lead to a more comprehensive investigation into why these biases manifest, why they are specific to certain subsamples, and why their magnitude and direction vary. This serves as a tangible demonstration of how a deeper understanding of endogeneity can pave the way for deeper insights and advances in understanding the inner structure of some data.

It is worth noting that this approach could also lead to a more cautious, but honest solution: simply focusing on the subsample where the evidence is more robust, and highlighting the subsamples where results are not confirmed or subject to over- or under-estimation bias. This approach could foster the promotion of new research opportunities. Revealing the intricacies of endogeneity within a dataset has the potential to inspire further discourse in future studies. As the complexity of the problem becomes clearer, researchers are more likely to explore alternative solutions, thereby propelling the field forward. In simpler terms, shifting the focus from understanding and elucidating the endogeneity issue to simply offering ready-made solutions might lead to superficial future interpretations and overlook the fundamental mechanisms behind a phenomenon. Elucidation of the endogeneity problem can offer valuable insights into the underlying theoretical mechanisms that drive certain phenomena. This, in turn, facilitates synergies between new theoretical developments and empirical research, which can be highly beneficial to the scientific community.

2.4. Theory and empirical identification: A loop

At this stage of our discussion, it is important to summarize the two main drawbacks we have highlighted thus far: i) a lack of clarity regarding the costs associated with achieving a more precise causal identification, and ii) an oversight in analyzing the endogeneity issues related to specific focal data. These two points are key because they could introduce biases in the symbiotic relationship between theories and empirical validation, generating also forms of superstitious learning in research trajectories (Levitt and March, 1988; Zollo, 2009).

In a significant portion of management research, theory is constructed as a framework comprising logical relationships (Beall and Logan, 2017) articulated into hypothesis statements that often include a causal implication among variables (Durand and Vaara, 2009). While a theory might maintain logical consistency in its hypothesis formation, its scientific legitimacy is significantly given by empirical causal identification, crucial for substantiating the theory as a viable explanation of a phenomenon.

As can be seen, the interdependence between theory and empirical causal identification

is pivotal. As empirical validation improves the precision of causal testing, a theory gains legitimacy and becomes a key framework for interpreting a focal phenomenon in future studies. However, two primary concerns arise, which are outlined at the start of this paragraph. First, as causal tests become more precise, they often rely on new assumptions and entail various limitations. Consequently, while the theory could gain credibility as a whole, it was empirically proved only within a specific set of assumptions. Secondly, when solutions are applied without considering the breadth and nature of endogeneity across the entire sample, empirical validation might obscure critical information or provide averaged results that do not accurately represent the entire sample. Again, the theory could acquire too wide a legitimacy.

Neglecting these matters could lead to a phenomenon similar to superstitious learning in scientific communities (Levitt and March, 1988; Zollo, 2009), where a partial identification of causality reinforces the credibility of the theory well beyond its limits. In other words, this process could create pseudoscientific narratives in which the misinterpreted boundaries of causal identifications lend undeserved scientific weight to a theory. As a consequence, multiple contradictory theories might hold similar legitimacy in explaining a single observed outcome. This scenario often results in limited mutual recognition among different scientific communities, where each presents its unique interpretations and perspectives, leading to closed debates within their own silos. Filatotchev et al. (2024) for example has defined this process as *semiotic abduction* in management research.

3. Conclusions

The field of management research has seen an increasing discourse on the pivotal role of theory and its empirical validation, marking a significant stride toward a more comprehensive understanding of the possibilities and limitations within this domain. Numerous articles have been instrumental in enriching the management literature by focusing on key aspects such as the nexus between theory and empirical evidence, the costs associated with identification, and the need for replication studies (Agarwal and Hoetker, 2007; Birkinshaw et al., 2014; Ethiraj et al., 2016; Arora et al., 2016; Bettis et

al., 2014).

This article actively engages in this evolving dialogue with the primary objective of raising fundamental questions about causality identification, its costs, and its connection to theory. At the heart of management (but not only management) research lies the interdependent relationship between causal identification and a theory's legitimacy. This article navigates this issue by initially delving into the complexities of causal identification and exploring recent methodologies employed by researchers to solve endogeneity. Then it highlights the costs related to identification, such as the introduction of additional assumptions and constraints on generalizability. Moreover, the article advocates for a wider adoption of tests dedicated to investigating endogeneity within datasets before proposing remedies. It argues that endogeneity could not be uniformly distributed across samples. Therefore, a comprehensive analysis of the magnitude, direction, and varying impact of biases on different sample observations could provide deeper insights into the legitimacy of the theoretical mechanisms.

The article particularly emphasizes how opacity in these assessments may lead to superstitious research trajectories generated by an unwarranted extension of theory legitimacy. According to this perspective, endogeneity plays a crucial role when understood thoroughly, and researchers should exercise caution before hastily connecting data analysis with their theoretical constructs. Researchers must conscientiously take into account the contexts and limitations within which they can substantiate a causal relationship between two variables, (Y) and (x), within a given dataset. Nevertheless, as previously discussed, causal identification could have important limitations, which if remains opaque could create superstitious trajectories. This superstitious process could empower a focal theory to offer the basis of new exploitative research, of prescriptive and predictive insights, guiding actions and decisions across different domains well beyond its limits.

One of the main points of this article is that examination of endogeneity within a specific sample should be a priority. Researchers should consider the magnitude, direction, and differential impact of bias, as understanding these facets can lead to more informed research outcomes. Recent methods employing nonnormal or bunched control variables

offer insight into these aspects, although they may not provide definitive solutions (Khalil and Yıldız, 2022; Park and Gupta, 2012).

In a grander scheme, the interplay between endogeneity and theory has the potential to fuel new research and lead to deeper insights. In this sense, it could promote discussions about different solutions, foster more replication studies, encourage a finer understanding of root causes, and open the door to more creative theoretical developments.

As a second pointmark, this article underscores the critical importance of considering endogeneity in research, as it is closely tied to the type of theory that can be sustained. It highlights the following points that merit further discussion and exploration:

- Exploring the nature of endogeneity can serve not only as a method to balance the trade-off between the precision of causal identification and the cost-effectiveness of solutions, but also as a valuable source of information for enhancing new theory development. The article suggests that the management community should strive to better tilt the balance toward assessing the nature of endogeneity problems rather than rushing into proposing consolidated solutions.

- Reducing potential opacity and clarifying the empirical boundaries of causal identification should coincide with advocating for replication studies and thorough meta-analyses, especially in data subsamples where endogeneity appears to exert significant influence.

- The article emphasizes the importance of simultaneously implementing these two approaches to enhance coherence in dialogue among diverse scientific communities.

However, it is important to note that some caveats should be raised regarding certain arguments presented in this article. The article provides an *average* portrayal of an evolving debate within management communities, offering a broad perspective with a static snapshot. As a result, it may not be exhaustive in its coverage and may not delve into the finer details and heterogeneity present in this debate, especially from an econometric point of view. Future contributions could clarify arguments that, because of the nature of this work, were left in the background.

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