THE METHODOLOGICAL LANDSCAPE OF INNOVATION MANAGEMENT RESEARCH: A CRITICAL REVIEW AND EMPIRICAL DEMONSTRATION

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Abstract

This paper presents a preliminary examination of contemporary methodological approaches in innovation management research, with a particular emphasis on statistical techniques and research designs. A systematic review of recent high-impact studies revealed a predominance of observational designs and cross-sectional data, with Confirmatory Factor Analysis (CFA) and the PROCESS macro emerging as popular analytical tools. We critically examine the limitations of these approaches, with a particular focus on their ability to establish causal relationships. To illustrate the influence of variable definition on innovation research, we present an empirical analysis of a large cross-sectional dataset, comparing different operationalisations of innovation. Our findings demonstrate that the results of studies on innovation vary considerably depending on the definition of innovation used. This highlights the need for more rigorous and consistent methodological approaches in the field. In conclusion, we advocate for the increased utilisation of experimental and quasi-experimental designs to enhance causal inference in innovation management research.

Key words: causal inference, observational data, variable operationalization, Factor Analysis

JEL Code: O32, C18, L25

Introduction

The domain of business research, development and innovation (R&D&I) management represents a fundamental pillar for the success and growth of any organisational entity. An innovative culture is a significant driver of organisational growth, fostering creativity and competitiveness. Statistical analysis is a powerful tool for uncovering insights, trends, and patterns within datasets, thereby providing valuable information for decision-making processes. By examining the specifics of statistical techniques, researchers can improve their capacity to derive meaningful insights from intricate data sets pertaining to innovation processes at the organisational level. The principal aim of this article is to collate and examine the prevailing methodologies for estimating and designing research in the field of R&D&I, and to demonstrate the sensitivity of this area to the definition of the dependent variable (innovative company).

Innovation management can be defined as the systematic process of creating, implementing, and monitoring innovative initiatives within an organisational context. This strategic approach encompasses the identification of novel concepts, the development of innovative solutions, and the implementation of these concepts to drive growth and competitive advantage in the market. Statistical methods comprise a diverse array of techniques employed for the analysis of data, the identification of patterns, and the drawing of meaningful conclusions from research findings. The utilisation of statistical instruments, including regression analysis, hypothesis testing and variance analysis, enables researchers to quantify uncertainties, identify trends and validate hypotheses, thereby facilitating evidence-based decision-making in the field of innovation management. The fundamental methodology, founded upon descriptive statistics and their visualisation, offers a means of summarising and reporting on the quality of data.

Inferential statistics represent the optimal approach. It enables the drawing of inferences and the making of predictions about data. This approach enables researchers to generalise findings to a larger population based on the analysis of sample data. In the field of economics, research design strategies may be distinguished as either observational or experimental in nature. Regression is employed in the analysis of observational R&D&I data, as exemplified by Community Innovation Surveys (Vokoun & Dvouletý, 2022). In the absence of random assignment, the causal interpretation of regression estimates is not guaranteed. Conversely, the experimental ideal (Angrist & Pischke, 2009), which employs a relatively complex random assignment, is more conducive to a causal interpretation. The term 'causality' is too multifaceted and complex to be used in this context; it is therefore typically referred to as 'experimental causality' or 'interventional causality'.

This form of causality is based on the premise that if an independent variable (the treatment) is manipulated while other factors are held constant, changes in the dependent variable can be attributed to the treatment. The process of random assignment is, in itself, a rather complex one. In order to ensure that there is no imbalance in the covariates across the groups that have been treated and those that have been placed under control, a number of strategies are employed. Nevertheless, even stratified randomisation based on company size and industry sector can prove problematic, as small companies may be included in the group of companies or partnership enterprises with more than one main economic activity. Furthermore, estimation requires the use of a set of control variables and a complex context analysis based on the industrial organisation context. This is to ensure that the "rerandomization of units" and final "balance" are achieved and that the experiment is "random and robust enough" (Morgan & Rubin, 2012).

The most recent literature on experimental design employs quasi-natural experimental design with causal inference, utilising a difference-in-differences (D-in-D) approach for the assessment of policy effects and randomised experiments (between-person design). A quasi-natural experiment design was employed to examine the effects of a policy implemented in Italy at the end of 2012 that favoured young innovative start-ups (Mellace & Ventura, 2023) and in Korea (Jang et al., 2024). This involved the use of DID to assess the impact of reducing legal working hours on firms. There has been a paucity of recent papers that are directly aimed at randomised experiments (between-person design) in the field of innovation management over the past year. The causal effects of leader ambidexterity on follower ambidexterity and innovative performance were estimated using randomised experimental methodology (Klonek et al., 2023).

The observational dataset designs and case-study designs that have emerged in recent managerial and innovation economics literature are based on ordinary least squares regression, limited dependent variable regressions and mixed qualitative and quantitative methods approaches as well as factor analyses (Corbo et al., 2023; Felicetti et al., 2024). Additionally, the number of control variables employed appears to be increasing. For instance, the research concerning digital transformation and enterprise innovation (Liu et al., 2023) utilises 17 control variables that address organisational demographics, financial ratios, and board structure. Furthermore, the partial least squares (PLS) approach for structural equation modelling (SEM) is a popular method for testing multiple hypotheses within proposed conceptual frameworks (Chatterjee et al., 2023). The three-stage Crépon-Duguet-Mairesse model is also employed to map the innovation process with a focus on panel datasets (Mendoza, 2024). The novel method of estimation is the Method of Moments Quantile Regression (MMQR), which has been employed in the field of environmental innovation research (Ramzan et al., 2023).

The Method of Moments Quantile Regression appears to offer a promising approach to innovation research, with several potential advantages. This approach permits a more comprehensive examination of the relationship between variables across different quantiles of the dependent variable, thereby facilitating insights into the manner in which factors influence innovation outcomes at various levels. The MMQR is particularly advantageous when dealing with heterogeneous effects and non-normal distributions, which are prevalent in innovation data. The method is robust to outliers and can capture non-linear relationships, thereby making it an appropriate means of studying complex innovation processes. Furthermore, MMQR is more effective than traditional regression methods in addressing endogeneity issues, thereby producing more reliable estimates in the presence of potential simultaneity or omitted variable bias.

Methodology

The initial section of the results comprises a conventional literature review based on filtered results from the Web of Science Core Collection and the Social Science Citation Index. The objective is to examine 10 articles published between 2023 and 2024 in the field of business or economics. A total of 181 results were identified based on the search terms "innovat* and manag* and regress*" and the highest background citation class sorting. The objective of this section is to conduct a preliminary investigation through a pilot survey of ten highly cited articles from top-quartile journals, with the aim of mapping the methods, data, and results and presenting them in a table. The standard simplified PRISMA approach will be assumed, and the number of screened papers will be reported. The screening process will employ a combination of subjective relevance and objective top quartile ranking, as well as the paywall barrier of the journal in question.

The second part will demonstrate the extent to which this field is sensitive to the different definitions of an innovative company. A published dataset will be employed to illustrate the discrepancies in the probability of innovation (Vokoun & Dvouletý, 2022) based on four modes of innovative company definition on the Czech, Hungarian and German datasets in 2014. The dependent variables will be defined as follows: (1) any non-zero R&D expenditures in the year of survey, (2) production process innovation, (3) new-to-the-firm innovation in the last three years, (4) new-to-the-market innovation in the last three years. The estimation process will be based on probit with marginal effects at means, with robust standard errors identified in accordance with the methodology set forth by Vokoun and Dvouletý (2022).

Results

A review of articles in the first quartile journals yielded somewhat unexpected results (Table 1). It was observed that none of the top 10 articles, as identified by background citations between 2023 and 2024, employed an experimental or quasi-experimental design. Of the 35 documents scanned, only 10 were directly focused on innovation activities within companies. The 25 articles were excluded from the review as they were not in the first quartile or were not directly relevant due to their focus on, for example, carbon emissions or environmental policies. The remaining ten articles were inaccessible due to the presence of a robust paywall, rendering them inaccessible through the utilisation of multiple Czech academic libraries.

Tab. 1: Statistical Methods in Innovation Management

Paper	Methods	Data and design	Dimension
Wang et al. (2024)	Confirmatory factor analysis	Firm questionnaire, cross-sectional data (286 Chinese firms, 65,15% return ratio)	Firm level, observational
Sakariyahu et al. (2023)	Pooled OLS, GLM, MM-QR	Firm questionnaire, pooled cross-sectional World Bank datasets (589 African firms, unknown ratio)	Firm level, observational
Bettiol et al. (2023)	two-step regression, “PROCESS”	Firm questionnaire, cross-sectional data (137 Italian firms, unknown return ratio)	Firm level, observational
Xu et al. (2023)	Confirmatory factor analysis, “PROCESS”	Firm questionnaire, cross-sectional data (619 Chinese firms, 77,7% return ratio)	Firm level, observational
Lazzarotti et al. (2023)	SPSS macro “PROCESS”	Firm questionnaire, cross-sectional data (250 firms from 4 countries, 3% return ratio)	Firm level, observational
Menter et al. (2023)	Fixed-effects OLS	Firm secondary data and press releases, panel data (German stock exchange, 60 out of 160 listed)	Firm level, observational
Zhang & Liu (2024)	quadratic assignment, hierarchical clustering	Firm secondary data, cross-sectional data (Chinese state-owned companies)	Firm clusters, observational
Borodako et al. (2023)	confirmatory factor analysis	Firm questionnaire, cross-sectional data (3135 Polish firms, 3.81% return ratio)	Firm level, observational
Qutaishat et al. (2023)	confirmatory factor analysis	Firm questionnaire, cross-sectional data (directly selected 60 Jordan companies)	Firm level, observational
Tiwari et al. (2023)	PLS-SEM	Firm questionnaire, cross-sectional data (151 Indian firms, 25% return ratio)	Firm level, observational

The most prevalent approach is confirmatory factor analysis (CFA), utilising data sets comprising between 137 and 3,135 companies, with a return rate spanning 3% to 65.15%. The authors contend that data samples comprising fewer than 300 companies lack sufficient representativeness. They also assert that a return rate of approximately 3-10% is deemed "fair," yet this is not considered a noteworthy success. The authors identify this as a potential limitation or weakness of their paper. Two papers employed OLS in multiple regression on samples that were not very representative. The first dataset is that of the World Bank, which represents the whole African region rather poorly, with a total of 589 companies included in the sample. The authors in second OLS paper intentionally selected a group of 60 listed companies that published their financial data using a single platform that provides secondary data, among 160 companies. This resulted in limited results and little insight into the innovation activities of listed companies. It would be beneficial for the authors to analyse their financial statements from other platforms or published annual reports.

A second analysis within this paper provides an operationalisation analysis on a cross-sectional large international sample (Tab. 2), demonstrating that different results can be obtained when considering the novelty or type of innovation activities. The results consistently indicate the significance of innovation activities. However, the specific outcomes may vary contingent on the definition of innovators. The initial model employed by the authors identifies innovators based on non-zero R&D expenditures, thereby estimating the probability of a company being classified as an innovator. There are notable discrepancies between the models, the level of novelty (new-to-the-firm vs. new-to-the-market), or the use of production process innovation as a proxy for an organisation being an innovator.

Tab. 2: Variable operationalization: a case study

	(1)	(2)	(3)	(4)
	All R&D	Production process	Firm	Market
Size: Medium (50-249)	0.302***	0.318***	0.0763**	0.109***
	(0.027)	(0.028)	(0.034)	(0.036)
Size: Large (250+)	0.666***	0.740***	0.512***	0.462***
	(0.031)	(0.033)	(0.039)	(0.039)
Country CZE	-0.680***	-0.0555*	0.890***	0.693***
	(0.029)	(0.030)	(0.040)	(0.039)
Country HUN	-1.081***	-0.667***	0.527***	0.847***
	(0.030)	(0.032)	(0.047)	(0.048)
Market orientation: National	0.564***	0.339***	0.452***	0.714***
	(0.031)	(0.032)	(0.035)	(0.041)
Market orientation: European	0.614***	0.471***	0.418***	0.807***
	(0.038)	(0.038)	(0.050)	(0.054)
Market orientation: World	0.959***	0.519***	0.478***	1.103***
	(0.050)	(0.053)	(0.057)	(0.060)
Herfindahl index	0.0000387***	0.0000394***	0.0000521***	0.0000386***
	(0.0000090)	(0.0000094)	(0.000011)	(0.000011)
Constant	-0.985***	-1.307***	-0.729***	-1.467***
	(0.032)	(0.034)	(0.033)	(0.040)
Observations	17381	16818	8168	8079

The papers in our sample do not employ a specific approach to identifying novelty or the type of innovation process, with the exception of Wang et al. (2014). The authors do not identify innovation activities by using levels of novelty; instead, they employ a more general understanding of their innovation variable (see Table 3). As they do not consider novelty, the replication of their research may be challenging, as different researchers may have disparate conceptualisations of technological innovation or innovation collaboration. Variations may exist in the form of collaboration on new-to-the-market projects or new-to-the-firm projects. Research based on vague definitions is inherently difficult to compare.

Tab. 3: Variable operationalization: current research

Paper	**Innovation variables and specific novelty or market impact defined in innovation variables.**	
Wang et al. (2024)	Exploratory and Exploitative Innovation Outputs	Defined
Sakariyahu et al. (2023)	Technological innovation	Undefined
Bettiol et al. (2023)	Collaboration, breadth and depth of technologies	Undefined
Xu et al. (2023)	Technological innovation, Bricolage	Undefined
Lazzarotti et al. (2023)	Collaboration	Undefined
Menter et al. (2023)	Business Model Innovation	Undefined
Zhang & Liu (2024)	Technology Proximity, Collaboration	Undefined
Borodako et al. (2023)	Innovation Orientation, Knowledge Management, Technological Readiness	Undefined
Qutaishat et al. (2023)	Innovation Orientation, Knowledge Management, Technological Readiness	Undefined
Tiwari et al. (2023)	Innovation Orientation, Knowledge Management, Technological Readiness	Undefined

Discussion

Confirmatory factor analysis (CFA) is a multivariate statistical procedure that is theory-driven and is used to assess the construct validity of latent variables and their indicators. In contrast to exploratory factor analysis, CFA necessitates that researchers stipulate the number of factors and the pattern of indicator-factor loadings in advance, based on theoretical considerations or prior empirical evidence. CFA typically employs cross-sectional data gathered through surveys or archival sources. The dataset comprises observed variables (indicators) that are presumed to represent underlying latent constructs. The assumptions are quite strict. The indicators must be multivariate normally distributed, there must be no multicollinearity, the sample size must be adequate (generally N > 200), and the model specification must be correct. Furthermore, the indicators must be measured continuously or ordinal. These assumptions are typically relaxed with regard to model specification, given that the models in question are often relatively simple. The CFA model can be misspecified due to researcher bias and the unavailability of control variables. The primary limitation is the inability to capture dynamic relationships in cross-sectional data.

PROCESS is a widely used computational tool for SPSS and SAS, developed by Andrew F. Hayes, designed for estimating direct and indirect effects in mediation and moderation models, as well as their combination in conditional process analysis. The PROCESS macro, written for the SPSS software, is typically used with cross-sectional data, which lacks the dynamic aspects of panel datasets. The dataset should include variables representing the independent variables (X), the dependent variables (Y), the mediators (M), and the moderators (W), along with any relevant covariates. Once more, the assumptions are quite strict. They include linear relationships between variables (which may not always hold true), normal distribution of residuals (usually relaxed to some extent), homoscedasticity, absence of multicollinearity, and proper temporal precedence (presumed) in mediation models. The main limitation is the strict use of continuous variables, which are difficult to obtain, and the assumption of linear relationships between them and the dependent variable.

The CFA and PROCESS methods are valuable for exploring relationships between variables. However, their use for causal inference from cross-sectional data is highly problematic. It would be prudent for researchers to exercise caution when making causal claims based solely on these analyses, and it is similarly advisable for reviewers and readers to subject such claims to critical evaluation. These methods can suggest potential causal relationships; however, they are unable to establish causality from cross-sectional data. Furthermore, there is no means of addressing the reverse causality issue, which is a limitation of cross-sectional designs. In the most favourable scenario, they can test the consistency of the data with a hypothesized causal model, potentially rule out some alternative explanations and provide suggestive evidence that may inform future experimental research.

This paper sets out to examine the ways in which experimental designs can be employed in the field of innovation economics. The most challenging aspect of this methodology is the allocation of companies to either the treatment or control group. It is not within the remit of researchers to direct business strategies. However, strategies may be employed at the level of economic policy. The objective of economic policies is typically to benefit micro, small and medium-sized companies. It is possible to randomly assign publicly supported innovative or start-up companies to treatment groups. These groups may be offered a variety of interventions, including mandatory innovation workshops (which may cover topics such as readiness assessment, design thinking, trends and customer journeys, innovation road mapping, and so on) and examples of best practice. Alternatively, they may be invited to participate in industrial-specific productive failure workshops, or to gain project management certification for key managers. The list of potential treatments is extensive. Subsequently, it is possible to ascertain whether this "treatment" results in, for example, an increased efficiency of public support. Furthermore, it is possible to ascertain whether this approach results in higher success rates for start-ups and a more favourable overall innovation culture within the organisation. Furthermore, by examining the long-term effects of these interventions, it is possible to determine whether and in which industries they contribute to market growth and competitiveness. This comprehensive evaluation will shed light on the efficacy of innovation facilitation “workshops” and project management certification programmes in fostering innovation within businesses.

Conclusion

Our review and empirical demonstration highlight several crucial issues in the methodological landscape of innovation management research. Firstly, the prevalence of observational designs and cross-sectional data, while offering valuable insights, significantly constrains the ability to draw causal inferences. Despite their merits in examining intricate relationships, popular techniques such as CFA and PROCESS are constrained by their dependence on cross-sectional data and rigorous assumptions.

Secondly, our empirical analysis demonstrates the sensitivity of the results to the definition of innovation. The considerable discrepancies observed between different operationalisations of innovation underscore the necessity for greater precision and consistency in defining and measuring innovation in research. In light of these findings, several recommendations can be put forth to advance the field: It is recommended that researchers endeavour to employ a greater diversity of methodological approaches, integrating experimental and quasi-experimental designs wherever feasible to enhance the robustness of causal inferences. When employing observational data and CFA, researchers must exercise greater caution in their causal claims and be more transparent about the limitations of their methods. It would be beneficial for the field as a whole if there were greater standardisation in the definitions and measures of innovation employed, thus enhancing comparability across studies. It would be beneficial for future research to investigate the potential of longitudinal designs and advanced statistical techniques that can more effectively capture the dynamic nature of innovation processes.

In conclusion, while current methodological approaches have made a significant contribution to our understanding of innovation management, there is substantial room for improvement. By addressing these methodological challenges, researchers can enhance the rigour and relevance of innovation management research, ultimately providing more reliable insights for both theory and practice.

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