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Why do we need causal inference in scientometric research?

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ABSTRACT

This paper reviewed the fruitful achievements in the science of science, sociology of science and economics of science, and their benefits to scientometric research. Then, the causal inference was introduced, which has the potential to shape scientometric research by determining the cause and effect among variables. In the end, we proposed two detailed reasons why we need causal inference in scientometric research: (1) correlation-based scientometric research is not sufficient to support science & technology policy; (2) Scientometrics needs to go beyond metrics by explaining the mechanisms in science.

KEYWORDS

Causal Inference; Scientometrics; Science of science; Economics of science; Sociology of science

1 Introduction

Scientometrics is the "quantitative study of science, communication in science, and science policy" (Hess, 1997). Its development is based chiefly on the contributions of Derek J. de Solla Price and Eugene Garfield (Nalimov & Mulchenko, 1969; Garfield, 2009). In 1963, earlier before he published his milestone book *Little Science, Big Science*, which laid a theoretical foundation for Scientometrics research, Price met and started a lasting collaboration with Garfield, who created the Science Citation Index and made it possible to conduct quantitative research on scientific publications and their connections. In his milestone lecture "The Scientific Foundations of Science Policy" given in 1965, Price observed that as science grew exponentially, it presented new challenges to policy-makers and that they could be helped by the kind of Scientometric work he was carrying out and promoting (Nature, 1965).

Scientometrics has developed towards research evaluation and measurements during the past half a century, without many breakthroughs in research methods or techniques. On the one hand, scientists generate vast amounts of data in their research activities: papers and patents and their use, project applications, peer-review comments, etc., under data-driven science (Chen et al., 2022; Islam et al., 2022). Along with the industrialization of science, more and more datasets are available online, such as Scopus, PubMed, Google Scholar, Microsoft Academic Graph (MAG), and the U.S. Patent. The increasing data availability enables data-driven research targeting scientific literature and scientists (Fortunate et al., 2018; Zeng et al., 2017). In this case, the science of science (SciSci) stands out and overshadows Sciento-

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metrics by publishing in journals with a wide readership, such as *Nature, Science*, and the *Proceedings of the National Academy of Sciences of the United States.*

Bernal (1939), as the pioneer of SciSci, systematically illustrated the function of science, planning science, and the relationship between science and politics. His milestone book, *the Social Function of Science*, has profound significance across the scientific community. The newly rising SciSci discussed by Albert-László Barabási (Fortunato et al., 2018; Sinatra et al., 2016; Wang et al., 2013) & Dashun Wang (Yin et al., 2021), James Evans (Wu et al., 2019; Xu et al., 2022), Brian Uzzi (Yang et al., 2022; Jin et al., 2021), et al. in the past decade, differs Bernal's SciSci in that big data dominates their research. SciSci aims to quantify scientific behaviours, uncover predictable patterns, understand the mechanism driving science, and reformulate policies to stimulate innovations (Bourdieu, 2014; Zeng et al., 2017). According to Fortunate et al. (2018), the five topics of the SciSci include (1) network of scientists, institutions, and ideas; (2) problem selection, e.g., productive tradition or risky innovation, as discussed by Kuhn (1977) and Bourdieu (1975); (3) novelty, as measured by the Z score based on the co-citation relationship of journal pairs in references (Uzzi et al., 2013); (4) career dynamics, including funding allocation, tenure track, gender inequality, scientific mobility, etc.; (5) team science.

On the other hand, Scientometrics is known for uncovering "what", including patterns and laws in science, e.g., interdisciplinarity is associated with scientific innovation, rather than explaining mechanisms in science, e.g., how interdisciplinarity affects scientific innovation. The causal inference method in economics may address the causality between the two variables.

Economists also target scientific literature in their research ever since World War II (Nelson, 1959; Hicks, 1995), which is the core of economics of science (EcSci). The developing process of the EcSci can be classified into two phases: the traditional EcSci and the new EcSci. From the 1950s to the 1980s, the former acknowledged that knowledge of science contributed to technological change (Arrow, 1962; Nelson, 1959). Note that this is a simple linear relationship between science and technology development. However, this statement could not support the evidence that Japan, whose fundamental subjects are weak, owns prominent technology. Since the 1980s, the latter has been proposed to improve the classic approach of Arrow and Nelson (Partha, 1994).

The differences between traditional and new EcSci mainly display in three aspects. Firstly, the economists disproved the theory proposed by Arrow and Nelson. Hicks (1995) found that the large corporation published as many articles in American journals as a medium-sized research university. Secondly, the scholars utilized the methods from economics or theories from other disciplines to explore the mechanism of academic activity. Economists introduced the theory proposed by sociologists Merton and Merton (1968) to examine the mechanism of the scientific award system and found that there exists a phenomenon called winner-take-all, which makes the competition among scientists fiercer. Lastly, economists began to explore the relationship between science, innovation, and economic growth. For instance, Funk and Owen-smith (2017) proposed a CD index to quantify the degree of technological change. Azoulay et al. (2019) found that after the death of a star scientist, the flow of the articles by collaborators and non-collaborators decreased and increased by 8.6, respectively. Catalini et al. (2020) found that a low-cost airline can improve collaboration.

Apart from economists, sociologists also explain mechanisms in science by conducting epistemic practice and empirical research on "science", which is named the sociology of science (SocSci). It links science with social structure by using the "conceptual frameworks" of sociology. Different from historians of science who attributed the development of science to the intelligence of scientists, the sociologists focus more on the norms and organizations through which "science" is practised and explore the bidirectional causality between science and society, that is, how social factors influence science and how science affects society (Cole & Cole, 1973). When sorting out the development of the SocSci, we have to mention the most well-known sociologist Robert K. Merton and his enormous contributions to the discipline. His doctoral dissertation on the growth of science in England during the 17th century contains most of his research achievements, which profoundly impact his later studies (Merton, 1938; Cole, 2004). Merton (1968) published a milestone paper titled "The Matthew effect in science" in *Science*. Stephen Cole and Jonathan Cole, both of whom were students of Merton, are also prominent sociologists of science. They first introduced citation analysis into the scientific evaluation. They applied citation analysis to elaborate on social stratification in the scientific community (Cole, 1973). One of the exciting studies they have made is whether scientific progress is built on the labour of all "social classes" or is primarily dependent on the works of "elites". The Newton hypothesis believes that scientific progress "stands on the shoulder of giants." In contrast, the Ortega hypothesis argues that "experimental science has progressed thanks in great part to the work of men astoundingly mediocre, and even less than mediocre" (Ortega, 1932). Cole & Cole (1972) investigated three datasets made by physicists and the corresponding outstanding works and found evidence against Ortega's hypothesis.

SocSci differs the SciSci and Scientometrics in that it is theory-driven rather than data-driven. For example, Erin Leahey and her colleagues explored the impact of interdisciplinarity on scientists' research (Leahey et al., 2017). Instead of drawing conclusions and discussing potential implications from the data, they started this paper with the production and reception effect, based on which they proposed five hypotheses. Then, they tested the hypotheses by analyzing around 900 scientists and their 32,000 articles. At the end of the paper, they highlighted their contributions to organizational theory.

Scientometrics will benefit from examining causal inference to address the "how" and "why" questions on science. This paper highlights the importance of the counterfactual framework of causal inference as a research method in Scientometrics and explains the potential benefits.

2 Causal inference

The 2021 Nobel prize in Economics was awarded to David Card, Joshua D. Angrist, and Guido W. Imbens for their "Empirical research in the field of economics using causal inference" (https://www.nobelprize.org/). Causal inference uncovers causal relationships and provides clear implications to simple cause-and-effect questions in social science (Dunning, 2012, p. 3-14). For example, when we explore whether college education enhances future income, correlation analysis illustrates that people who attend college earn more on average than those who do not. However, many confounding variables are ignored in correlation analysis, such as personal ability, family background, social connections, etc. These factors make the estimates inaccurate. Nevertheless, casual inference can address this issue.

2.1 Experiments

The earliest experiments for causality happened. Fisher et al. (1923a, 1923b, 1923c) proposed randomized trials, which highlight the existence of causality and are the breakthrough in statistical methodology. Marshall (1948) introduced randomized controlled trials (RCT) about using streptomycin for pulmonary tuberculosis, deemed the first RCT in history. We utilize RCT, which is by far the most credible experiment, to overcome selection bias. An experiment is accomplished by randomly allocating subjects to two or more groups, treating them differently, and then comparing them concerning a measured outcome. The treatment group receives the assessed intervention, while the other, usually called the control group, does not. By randomizing the allocation process, we ensure that the control group and the treatment group are not systematically different from each other. In this way, we have an observed effect that equals the actual causal effect.

RCT has limitations: (1) conducting an RCT is often budget- and time-consuming, and (2) RCT is not applicable when it is contrary to ethics. For example, it is not ethical to randomly allocate volunteers to smoke if we use RCT to address the question, "is smoking harmful to our health?" In this case, an alternative method is a quasi-experiment.

2.2 Quasi–experiments

The quasi-experiment method was recognized when Rubin (1974) proposed the counterfactual framework. Subsequently, Angrist and Krueger (1991) outlined a new framework for causal inference in random assignment settings. They utilized instrumental variables, which economists have long used regression models with constant treatment. They found that the instrumental variables (IV) can be fitted into Rubin's causal model without assuming constant treatment effects. An example of IV in economic textbooks is to examine the relationship between compulsory school attendance and future income (Angrist & Pischke, 2009). Both variables are associated with latent variables, including personal ability, effort, family background, etc. Angrist and Krueger (1991) used the birth quarter as an IV for compulsory school attendance because a person's birth quarter is not associated with her ability, effort, or family background but differentiates the years of education[1].

Thistlethwaite and Campbell proposed (1960) regression-discontinuity design (RDD) to evaluate the effectiveness in social sciences. Economists have attempted to reinforce related theories and normalize the application forms (Hahn et al., 2001), which makes this method more widely used in social sciences (Imbens & Kalyanaraman, 2012). RDD is the most similar to RCT. The core idea of this method is that individuals near the cutoff point formed by policy intervention are similar and comparable. Then, differences in outcomes between individuals on both sides can be attributed to policy interventions. RDD is extensively utilized to evaluate educational policy (Angrist & Lavy, 1999), retirement policy (Müller & Shaikh, 2018), social security policy (Bernal et al., 2017), Public finance and housing policy (Artés & Jurado, 2018). Ebenstein et al. (2017) estimated the effect of air pollution on life expectancy by using China's Huai river as the cutoff point, i.e., north China of the Huai river supplies a heating system, but south China does not. They found that when airborne particulate matter, especially matter smaller than PM_{10} , increased by 10-μg/m^3, life expectancy will be reduced by 0.64 years.

Rosenbaum and Rubin (1983) first proposed propensity score matching (PSM) to eliminate selection bias. The propensity score replaces multiple covariates with one score and balances the distribution of covariates between the treatment group and the control group.

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1 The compulsory laws in the United States require students to be at least six years old before January 1 of enrollment and remain in school until their 16th or 17th birthday, which compels students born at the start of the year to attend school longer than those who born at the end of the same year.

In 1915, Obenauer and von der Nienburg (1915) utilized differences in differences (DID) to explore the effects of the minimum wage law and introduced this method into economics. DID aims to estimate the treatment effect and compare the difference between pre-treatment and post-treatment. The treatment effect is that we subtract the change of the control group from the change before and after treatment. Note that DID assumes that the experimental and control groups must have the same trend before processing, which is called the "Parallel trend" or "Common trend" assumption.

3 Causal inference in scientometric research

3.1 Trend of using causal inference in scientometric research

Using "causal inference" and related methods such as "propensity score matching", "instrumental variables", "differences in differences", and "regression discontinuity" (including their abbreviations) as retrieval terms, we search the articles that use the causal inference method to conduct scientometric research in the Web of Science and the Chinese Social Science Citation Index (CSSCI) database, respectively. Figure 1 shows that (1) in general, related research is still in its infancy, i.e., the Web of Science database indexes 54 papers, and the CSSCI database includes only 10; (2) scientometric research using causal inference has increased significantly since 2019; (3) Chinese publications are less than English ones.

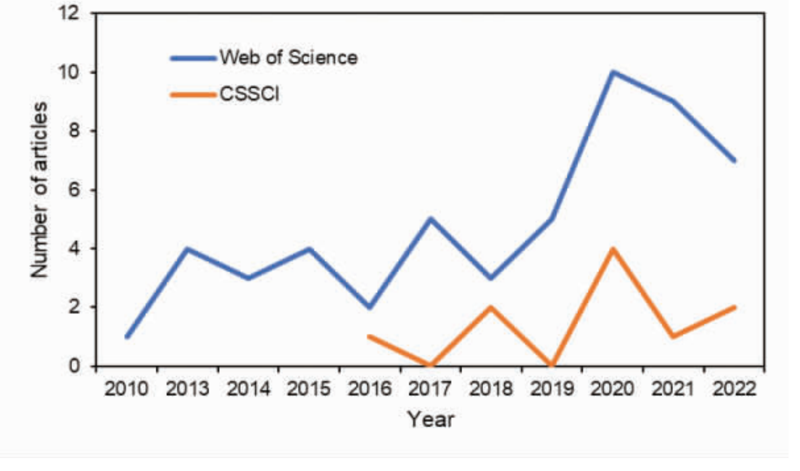

Figure 1 Number of articles using causal inference in scientometric research over years

3.2 Causal inference explains the causal relationship between variables in scientometric research

Before the introduction of causal inference to Scientometrics, the majority of scientometric research remained as descriptive statistics, hypothesis tests, correlation analysis, etc. To address the research question, "to what extent research funding contributes to scientists' successes? " a scientometric study may explore the association between research funding and future success chances by comparing the research performance of the scientists who were funded and that of the scientists who were not. However, there is selection bias in this research design because the scientists who were funded have more significant research potential than those who were not. In this case, the successes might be attributed to the scientists' research potential. A quasi-experiment design can eliminate this selection bias by comparing the research performance of the near-miss and the narrow-win scientists, as shown in the RDD by Bol et al. (2018) and Wang et al. (2019). The policy implication is obvious after they explain the causal relationship between research funding and career successes. Bol et al. (2018) won the Best Paper Award of ISSI 2019 because of their innovative research design.

To address another research question, "is there a bias towards authors' reputation in peer review?" a scientometric study may explore the correlation between authors' reputation and the acceptance rate of their submissions. However, there is selection bias in this research design because higher reputation authors might have more significant research potential, and their higher acceptance rate is attributed to their higher research potential to a certain extent. An RCT design can eliminate this selection bias by randomly designating a manuscript co-authored by a prominent (such as the 2002 laureate of the Nobel Memorial Prize in Economic Sciences) and a relatively unknown early-career scientist to reviewers in three different ways: (1) only the prominent author's name appearing in the manuscript, (2) an anonymized version of the paper, or (3) only the less early-career author's name appearing in the manuscript, as shown in Huber et al. (2022). As a result, significantly more peers accept the invitation to review the paper when the prominent author appears as the corresponding author. Then, there is solid evidence of bias toward authors' reputation in peer review.

4 Reasons why we need causal inference in scientometric research

4.1 Correlation-based scientometric research is not sufficient to support science & technology policy

Analysis of existing data shows that funded teams accumulate more citations than less-funded teams (Wuchty et al., 2007). Does it mean that science & technology (S&T) policy should be adjusted to allocate more funding to the former? The work of interdisciplinary teams received fewer citations (Sun et al., 2021). Should we discourage interdisciplinary research hence? We do not know whether the extra citations are brought by the funding or other factors, such as team size, authors' reputation, affiliations' reputation, etc. We do not know whether interdisciplinary teams of other factors, such as low research quality and low efficient collaboration, bring fewer citations. Therefore, it is risky to adjust S&T policy based on correlation results.

Instead, the causal relationship provides more solid evidence for S&T policy. For example, Bol et al. (2018) found the funding effect, i.e., "winners just above the funding threshold accumulate more than twice as much funding during the subsequent eight years as non-winners with near-identical review scores that fall just below the threshold", because non-winners may cease to compete for other funding opportunities. In this case, the S&T policy should be adjusted to raise the funding rate rather than to distribute the funding to a minority of applicants.

Nevertheless, the limitations of correlation analysis do not mean that science will abandon this method. Instead, correlation analysis uncovering associations between variables that have never been uncovered also reaches theoretical contributions. We observe the association between interdisciplinary research and scientific innovation (Leahey et al., 2017), then interdisciplinary research is encouraged in science policy in many countries. There are many patterns of interdisciplinary research which depend on the number of scientists, disciplines, genders, career stages, institutions, or countries involved. It is unnecessary to figure out the causal relationship between each pattern of interdisciplinary research and scientific innovation before issuing an encouraging policy. However, it does not mean that exploring the causal relationship is unnecessary. Instead, results based on causal relationships help us rethink the relationships between the two variables. For example, Liu et al. (2021) found that interdisciplinary collaboration research is less disruptive, as defined by Wu et al. (2019), than monodisciplinary research by using the method of matching.

4.2 Scientometrics needs to go beyond metrics by explaining the mechanisms of science

Wu et al. (2022) reviewed the development of SciSci and Scientometrics and linked metrics of science to mechanisms of science. In this paper, most of the metrics they concluded are from Scientometrics. However, most of the mechanisms are from the SocSci and the EcSci, such as the Matthew effect in science (Merton, 1968), the "black box of science" for concept establishment (Latour, 1987), the "burden of knowledge" for research collaboration (Jones, 2009), etc.

Scientometric indicators, such as the number of publications/citations, are usually used to measure scientific successes. An example introduced by Nature (2022) is that, according to this norm, scientific research has been very successful on Covid-19 because many related papers have been published and received many citations since its outbreak. However, research on Covid-19 has not achieved any breakthroughs so far. Therefore, there is a gap between the information conveyed by scientometric indicators and our understanding of science. The gap can be narrowed by explaining mechanisms in science. Causal inference is not the unique way to explain the mechanisms in science but an effective way of determining which variable is the cause and which is the effect. For example, Zhao et al. (2020) observed that Chinese returnees are more productive after they return to China. According to the results from PSM+DID, the mechanism beyond is that the higher productivity is caused by the research environment provided by Chinese universities and institutions.

It is not difficult for scientometric research to uncover the correlation between interdisciplinary research and scientific innovation. However, we know little about how interdisciplinarity affects scientific innovation from scientometric research. It is expected to explain the mechanisms of scientific innovation after uncovering the correlation between interdisciplinary research and scientific innovation to help us better understand science. One may argue that it is the job of the science of science, the EcSci, or the SocSci to explain the mechanisms in science. Nevertheless, scientometric research, which uncovers laws and explains mechanisms in science, is fascinating and attracts more young talents to this field.

5 Conclusions

We first reviewed the fruitful achievements in SciSci, SocSci, and EcSci, and their potential influence on scientometric research. Second, we introduced causal inference, including RCT and quasi-experiments. Third, we retrospectively reviewed the use of causal inference in scientometric research. Last, we concluded two reasons why we need causal inference in Scientometric research: (1) correlation-based scientometric research is insufficient to support science & technology policy; (2) Scientometrics needs to go beyond metrics by explaining the mechanisms of science.

Causal inference has excellent potential to shape Scientometrics by determining the cause and effect among variables and explaining the mechanisms of science. For example, a promising picture of scientometric research on interdisciplinary research and scientific innovation is that how interdisciplinarity affects scientific innovation is fully explained based on their correlation. In this case, science policy will target scientific innovation with higher precision. Casual inference goes beyond the metrics, descriptive statistics, and correlation between variables. Using open science and open data under data-driven science, Scientometrics has a bright future by diversifying research methods. The easiest way for scientometric research to achieve this goal is to ask "how" or "why" after we identify the correlation between two variables.

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Declarations

Conflict of interest. The first and corresponding author (Jiang Li) is a member of the editorial board of Data Science and Informetrics.

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