

Causal microeconometrics in accounting research

Mikroekonometria przyczynowa w badaniach w rachunkowości

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Abstract

Purpose: This paper reviews accounting research that employed causal inference methodology, with a focus on methods associated with causal microeconometrics (quasi-experimental). The reviewed papers were published in five leading accounting journals from 2017 through 2021.

Methodology/approach: The research approach is a literature review of studies that apply the methodology of causal microeconometrics to accounting. The main section of the paper describes five methods: the treatment effects approach, propensity score matching, natural experiment, difference-in-differences estimators, and regression discontinuity design. The assumptions and limitations of each method are discussed, and selected examples of causal inference published in five leading accounting journals are provided.

Findings: The study confirms the increasing frequency of the use of causal inference methodologies in accounting research. Sometimes referred to as quasi-experimental or causal microeconomic, these methods can provide a base for finding evidence of causality. However, there are limitations associated with each method.

Practical implications: Statistical-econometric methodology in accounting research based on regression is rarely able to demonstrate causal relationships. This paper presents the pros and cons of applying causal inference methodologies in accounting.

Originality/value: The paper's value lies in: (1) introducing to the research community the growing presence of quasi-experimental causal methodologies in accounting, (2) presenting causal research in accounting using causal microeconomic methods, (3) identifying papers using these methods that were published in five leading accounting journals between 2017 and 2021, and (4) highlighting the challenges and the need for caution and due consideration in applying these methods.

Keywords: causal inference, accounting research, causal microeconometrics, quasi-experimental methods.

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Streszczenie

Cel: Artykuł przeglądowy złożony z opisu oraz przykładów zastosowania metodyki wnioskowania przyczynowego w badaniach w rachunkowości. Koncentrujemy się na metodach zaliczanych do mikroekonometrii przyczynowej (quasi-eksperymentalnych). Przegląd zastosowań obejmuje artykuły opublikowane w pięciu renomowanych czasopismach naukowych z zakresu rachunkowości w latach 2017–2021.

Metodyka/podejście badawcze: Metodą badawczą jest przegląd literatury. Przedstawione są metody mikroekonometrii przyczynowej w zastosowaniu do badań w rachunkowości. Główna część artykułu opisuje metody oparte na koncepcji efektów oddziaływania, metodę *propensity score matching*, eksperyment naturalny, estymację metodą DiD: *difference-in-differences* (różnicy w różnicach) oraz RDD: *regression discontinuity design* (model regresji nieciągłej). Omawiamy również założenia i ograniczenia tych metod. Przedstawiamy także przykłady zastosowań metod wnioskowania przyczynowego z wybranych artykułów opublikowanych w pięciu czołowych czasopismach naukowych z zakresu rachunkowości.

Wyniki: Przegląd potwierdza rosnącą popularność metod wnioskowania przyczynowego w badaniach z zakresu rachunkowości. Do wykrywania przyczynowości służą m.in. metody quasi-eksperymentalne (mikroekonometrii przyczynowej). Jednakże, każda z metod ma rozmaite ograniczenia.

Praktyczne implikacje: Metody statystyczno-ekonometryczne oparte na analizie modelu regresji rzadko mogą dać odpowiedź na pytanie o związek przyczynowy. W tym artykule przedstawiamy argumenty za i przeciw stosowaniu nowych metod wnioskowania przyczynowego w obszarze rachunkowości.

Oryginalność/wartość: Oryginalność artykułu polega na: (1) wskazaniu rosnącej metodyki przyczynowej (quasi-eksperymentalnej) w badaniach z zakresu rachunkowości, (2) przedstawieniu metod mikroekonometrii przyczynowej w rachunkowości, wraz z ograniczeniami tych metod, (3) pokazaniu listy artykułów wykorzystujących te metody i opublikowanych w pięciu renomowanych czasopismach naukowych z rachunkowości w okresie 2017–2021 oraz (4) podkreśleniu wyzwań i ograniczeń związanych ze stosowaniem tych metod.

Słowa kluczowe: wnioskowanie przyczynowe, badania w rachunkowości, mikroekonometria przyczynowa, metody quasi-eksperymentalne.

Introduction

This paper presents how statistical-econometric methodologies are used in accounting studies to examine causality hypotheses. The applied methods are part of microeconometrics and are herein referred to as “causal microeconometrics”.

Research methodologies in accounting reflect its nature as a field of social science. As Oler et al. (2010) stated: “Accounting research may be broadly characterized as research into the effect of economic events on the process of summarizing, analyzing, verifying, and reporting standardized financial information, and on the effects of reported information on economic events”. As in economics, law, and other social science disciplines, the research methods in accounting encompass a plethora of approaches.

A broad presentation of accounting research methodology is beyond the scope of this paper. For discussions of methods used in accounting research, the reader is

referred to papers by Laughlin (1981), Oler et al. (2010), Coyne et al. (2010), Lopes (2015), Barrick et al. (2019), and Moon and Wood (2020), among others. Specific methodologies have also been discussed, e.g., accounting narratives, as presented in the entire issue of *Accounting and Business Research* (issue 6–7, vol. 45, 2015) and in the paper by Beattie (2014). Additionally, behavioral accounting research was discussed by Birnberg (2011).

In the last two or three decades, accounting research has undergone an “empirical revolution,” along with all the other social sciences (Floyd, List, 2016). In accounting, this has been a natural extension of new research streams in economics and finance. Major changes have resulted in the widespread use of experimental and quasi-experimental approaches for modeling causal relationships. The causal approach seems relevant for answering most research questions. However, as Armstrong et al. (2022) stated, researchers using this methodology must be extremely careful: “Reliable causal inferences require compelling economic theory, methods that make assumptions that comport with the institutional setting being studied, and a plethora of robustness tests to triangulate inferences across (often implicit) theoretical assumptions”.

“The empirical gold standard in the sciences is to identify a causal effect of some variable (or set of variables) on another variable”. This statement by Floyd and List (2016) appeared in their paper published in the “*Journal of Accounting Research*”. It is evident that most scientific research is aimed at this goal, and in recent years, the methodology of evidencing causality in economics has received the highest honors. The 2021 Nobel Prize in Economics was awarded to David Card, Joshua D. Angrist, and Guido W. Imbens for their contribution to analyzing causal relationships.¹ Abhijit Banerjee, Esther Duflo, and Michael Kremer received the 2019 Nobel Prize for their “experimental approach to alleviating global poverty”.²

In the accounting literature, there is a growing debate about the methods that make it possible to draw causal inferences. This debate is evidenced by the recent survey of Armstrong et al. (2022), as well as by discussions by Leuz (2022)³ and Whited (2022). An earlier much-cited paper by Gow et al. (2016) also includes the survey of causal inference methods applied in accounting. Floyd and List (2016) discussed how field experiments that were developed in economics might be more widely used in accounting research.

¹ David Card was awarded the Nobel Prize for his “empirical contribution to labor economics” in which he used natural experiments. He is co-author of a seminal paper with the late Alan B. Kruger on minimum wages and employment (Card, Kruger, 1994). The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2021: <https://www.nobelprize.org/prizes/economic-sciences/2021/summary/>.

² The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2019: <https://www.nobelprize.org/prizes/economic-sciences/2019/summary/>.

³ Leuz (2022) argues for a design-based approach to accounting research “that shifts attention from methods to the entire research design” (see Card, 2022).

The online book by Ian D. Gow and Tony Ding entitled “Accounting Research: An Introductory Course” devotes 6 of its 27 chapters to causal inference methods (current version 2023 https://iangow.github.io/far_book/index.html). Researchers interested in a deeper exposition of causal methodology can consult numerous sources, e.g., the online textbook entitled “Causal Inference: The Mixtape” by Scott Cunningham (current version 2023 <https://mixtape.scunning.com/>) or resources on the webpage of Joshua Angrist (<https://economics.mit.edu/people/faculty/josh-angrist>). The Society for Causal Inference (<https://sci-info.org>) provides additional resources for researchers.

The following section presents the field of microeconometrics and causal microeconometrics and its current use in accounting research. Subsequent sections illustrate methods of causal microeconometrics in accounting, including examples from leading journals.

1. Microeconometrics and causal microeconometrics in accounting

Microeconometrics is econometric modeling based on microdata, i.e., data about single companies, transactions, disclosures, and events. In his 2000 Nobel Prize lecture, James Heckman (2001) stated: “Microeconometrics is a scientific field within economics that links the theory of individual behavior to individual data where individuals may be firms, persons or households”. Today’s research in economics typically uses sets of microdata that represent the heterogeneity of agents (or, e.g., incidents). Therefore, these models are richer and better for characterizing individual decisions, choices, or situations.

Microeconometrics in accounting is termed “financial” owing to the nature of the subjects being studied. Financial microeconometrics is the research methodology applied in corporate finance and accounting. Practically all regression models that are used in accounting research represent the field of financial microeconometrics. Typical modeling is based on microdata from multiple companies.

Gruszczyński’s (2022) survey paper on econometric methods in accounting revealed that, out of 246 papers published in five leading accounting journals in the 2017–2021 period, two-thirds (165 papers) employed methodologies that fall within financial microeconometrics. The journals are: “British Accounting Review”, “Journal of Accounting Research”, “Journal of Accounting and Economics”, “European Accounting Review”, and “Contemporary Accounting Research”. The examined papers were published in selected issues of those journals, one issue from each year.

Major microeconomic techniques that are in use in accounting research include:

- regression on cross-section or time series data
- panel data regression
- qualitative variables models: binomial, multinomial, tobit, and sample selection

- causal microeconometrics models: treatment effects, difference-in-differences (DiD), propensity score matching (PSM), and regression discontinuity design (RDD).

The most common methodology is panel regression. These models were used in nearly 80% of all econometric papers, sometimes jointly with other approaches. Meanwhile, methods that may be encompassed within causal microeconometrics (quasi-experimental) appeared in approximately 20% of the papers.

Other surveys on quantitative methodology in accounting did not use microeconomic terminology. Armstrong et al. (2022) concentrated on publications from three journals between 2005 and 2019: “Journal of Accounting and Economics”, “Journal of Accounting Research”, and “The Accounting Review”. The major result is the upward time trend in the appearance of causal methodology in those journals, with the percentage of such papers rising from approximately 5% to 20% during that period. The authors discuss quasi-experimental methodologies, their connection to theory, and their drawbacks.

An earlier survey by Gow et al. (2016) analyzed papers published in 2014 in the same three journals. They found that 106 of 125 original research papers used observational data, and 91 of them “[sought] to draw causal inferences”. The methods applied were OLS regression, DiD and PSM. They did not indicate how many papers used each of those methods.

2. Methods of causal microeconometrics

Most econometric-type analyses in accounting discuss how a particular Y variable (explained, endogenous) is associated with other variables X (explanatory). This is a regression model, and the concept is close to correlation. After estimating the regression of Y with respect to X variables, a notion about how these variables are associated, and how strongly, is developed. For example, in a model where Y is firm performance and one of the X variables is the corporate governance level, the estimated coefficient X tells the researcher if and how these variables are associated within the sample of companies under consideration. When we need to prove that corporate governance affects firm performance, tools other than regression are needed. One solution is the “treatment effects” approach in which we compare a sample of companies that are “treated”, e.g., those that are subject to a new governance order, with companies that are “untreated”.

The techniques to properly verify causal effects are not straightforward and require adherence to assumptions that are not necessarily possible to adopt. Therefore, when we use regression, the only solid outcome may be evidence of how and how strongly the explanatory variables (X) are associated with the explained variable (Y).

The regression model remains valid as long as it is not used to prove causality. Correlation is not causality. Therefore, articles that claim to show the “impact” of X on Y by estimating regression equations are not correct. The only valid

interpretation of regression results should be expressed in terms of “association” or “relationship”.⁴

Section 1 notes an uptrend in accounting research studies seeking evidence of causal relationships by applying new methodologies. Most of these approaches are considered methods of causal microeconometrics or methods of *metrics* as dubbed by the “fathers” of these approaches, i.e., Angrist and Pischke in their seminal books published in 2009 and 2015 (Angrist, Pischke, 2009, 2015). Several of these methods are presented below.

The focus here is on methods that make use of data that occur naturally, e.g., data from companies’ financial statements, data published by statistical authorities, and data observed on financial markets. Another stream of causal research uses experiments (field experiments), but that topic is not addressed in this paper.

The following subsections quote several passages from Chapter 2 of Gruszczyński’s (2020) book on financial microeconometrics, as well as other sources. The essence of causal microeconomic methodology is briefly described, beginning with the notion of treatment effects. The examples were selected from published accounting research.

2.1. Treatment effect

A major concept in causal microeconometrics (or ‘metrics’) is the *treatment effect* (TE). Take the example of a company considering going public, i.e., undertaking an IPO. If it actually initiates an IPO, it is being “treated”; if not, it is “not treated,” i.e., it belongs to the *control group*. When making an IPO decision, the company expects its profitability to improve. The variable representing profitability is the result of the IPO. The TE is the difference (positive or negative) between the result when the company is treated and the result when the company is not treated. The TE will then represent the causal effect of going public.

However, each company will have two *potential* results, but only one result is observed, i.e., a particular company either goes public or it does not. The other result is *counterfactual*: it cannot be observed. To estimate the TE, two sets of data on companies are needed: one set for companies going public (IPO companies) and a second set for companies not going public (non-IPO companies). Except for the IPO decision, the second group should mimic the first as closely as possible. Larrain et al. (2023) treated IPO and non-IPO companies as those that have, respectively, completed or withdrawn IPO attempts. The withdrawn IPO attempts represent counterfactuals. The result variable, the measure of company profitability, is the operating return on assets (OROA = earnings before interest and taxes/book assets).

⁴ However, some regression-type approaches, like panel regression, especially with autoregression, come close to revealing causality. Nevertheless, we should remember that a “common regression (correlation) technique based only on observational data has no ability to evidence causality; [...] it has valuable interpretative value, especially when the sample includes companies properly fit to each other” (Gruszczyński, 2018).

There are various methods to estimate TE. Let us assume that the IPO decision of the i -th company is represented by the random variable D_i , with two possible values: 0 and 1 (i.e., $D_i = \{0, 1\}$ where 0 means “no” and 1 means “yes”. The potential result for the i -th company is:

$$\text{potential result} = \begin{cases} y_{1i} & \text{if } D_i = 1 \\ y_{0i} & \text{if } D_i = 0 \end{cases} \quad (1)$$

where y_{0i} denotes the result (e.g., OROA) for the i -th company, assuming that there is no IPO, regardless of what really happens. Similarly, y_{1i} denotes ROE for the i -th company, assuming that there is an IPO, regardless of what really occurs. The treatment effect for the i -th company would be simply $y_{1i} - y_{0i}$. What we observe in reality for the i -th company is

$$\text{either } y_i = y_{1i} \text{ if } D_i = 1 \quad \text{or} \quad y_i = y_{0i} \text{ if } D_i = 0 \quad (2)$$

and this can be written as

$$y_i = D_i y_{1i} + (1 - D_i) y_{0i} \quad (3)$$

where $D_i = 1$ if IPO and $D_i = 0$ if non-IPO. The average observed difference in OROA values (between companies with and without an IPO) is called the *average treatment effect (ATE)* and is equal to

$$ATE = E(y_i | D_i = 1) - E(y_i | D_i = 0) = E(y_{1i} | D_i = 1) - E(y_{0i} | D_i = 0) \quad (4)$$

The *ATE* can be easily computed. What we would like to know is the treatment effect “on the treated” (*ATT*), i.e., the change in OROA for companies deciding on an IPO compared to the same companies not deciding on an IPO. The right-hand side of (4) can be written as

$$\begin{aligned} ATE &= E(y_{1i} | D_i = 1) - E(y_{0i} | D_i = 0) \\ &= \{E(y_{1i} | D_i = 1) - E(y_{0i} | D_i = 1)\} + \{E(y_{0i} | D_i = 1) - E(y_{0i} | D_i = 0)\} \end{aligned}$$

So, *ATE* is the sum of two differences. The first is *ATT* (*average treatment effect on the treated*)

$$ATT = E(y_{1i} | D_i = 1) - E(y_{0i} | D_i = 1) \quad (5)$$

and shows the causal effect of an IPO in companies that actually decided on an IPO. This is the difference between the OROA for those companies (i.e., $E(y_i | D_i = 1)$) and the OROA for the same companies assuming (hypothetically) that they did not decide on an IPO (i.e., $E(y_{0i} | D_i = 1)$). We cannot compute *ATT* (5), but we can compute *ATE* (4), which can now be expressed as

$$ATE = ATT + \textit{selection bias} \quad (6)$$

where *selection bias* is the difference between the average y_{0i} for companies that did and those that did not decide on an IPO. We do not know the magnitude or the direction of the selection bias. The question is when the selection bias equals zero.

Firstly, it happens when variables D_i and y_i are independent. This is possible only for randomized experiments or a simple random sample. In our case, it would mean that companies are randomly selected, and they floated an IPO, or they did not. Another possibility for lowering the magnitude of selection bias is the matching of IPO and non-IPO companies, which ensures the independence of variables D_i and y_i , conditionally on the explanatory variables (“covariates”) X_i .

An additional concept in the treatment framework is *LATE* = *local average treatment effect*. This is a treatment effect that makes use of a dummy variable Z_i (*instrument*) that, in our example, equals 1 for companies considering (“being offered”) an IPO and 0 for the remaining companies. Companies that decide to consider an IPO are, as above, represented by the dummy variable D_i being equal to 1 for companies that have completed an IPO attempt and 0 for companies that have withdrawn an IPO attempt. *LATE* is the treatment effect calculated by Larrain et al. (2023).

2.2. Propensity score matching

The selection bias in equation (6) can be minimized when companies “with the treatment” and companies “without the treatment” have the same probability of treatment. This probability is called the *propensity score*. The *propensity score matching* (PSM) method makes it possible to create a comparison group by matching the “IPO” observations (companies) to the “non-IPO” observations for similar values of the propensity score. In this case, the score represents the “propensity of a company to be treated”. The general idea is to match “treated” to “non-treated” companies that are as similar as possible. Instead of matching against all the X_i variables, the match is performed with a single measure called the propensity score.

The propensity score can be estimated with the use of the binomial logit model with D_i as the explained variable and the covariates X_i as the explanatory variables. The estimated probability that $D_i = 1$ for each observation is the propensity score. After calculating the propensity score for each observation in the sample, the “treated” observations (with $D_i = 1$) are matched with the “untreated” ($D_i = 0$) that have the same or a very close propensity score. Finally, the *ATE* is calculated as the average difference between y_i for pairs of matched observations (with $D_i = 1$ and with $D_i = 0$).

PSM example

PSM results must be treated with caution. As pointed out by Shipman et al. (2017), the PSM “does not emulate experimental conditions and has limited external validity... PSM estimates can be fickle and difficult to replicate, indicating the need for stress testing matched sample results and supplementing PSM with alternative research designs”. They proposed a set of good practices for situations in which PSM can be useful.

The PSM was applied in research published in “Zeszyty Teoretyczne Rachunkowości” by Białek-Jaworska and Dec (2019). They verified whether the

financing of companies in Poland through intra-group loans affected earnings smoothing. Data constituted the panel of companies' financial statements for the period 2003–2014 (112,000 firm-years). The result variable (*smooth*) was the function of the standard deviation of net income before extraordinary items divided by the standard deviation of cash flow from operations (net income and cash flow are divided by total assets). The treatment group comprised companies with intra-group loan financing; the control group comprised companies without access to such financing. The explanatory variables included company size, ROA, debt, and leverage. The outcome shows that private companies financed by related entities exhibit significantly less earnings smoothing than other private companies, so there is a causal relation between intra-group financing and income smoothing.

2.3. Natural experiment and quasi-natural experiment

In some cases, the treatment effect can be computed “naturally”, i.e., when observations are allotted in a natural way to the treatment and control groups (Dunning 2012). Card and Krueger's (1994) famous study used a natural experiment to answer the following question: What are the employment effects of the minimum wage increase in New Jersey (NJ) effective April 1, 1992? Card and Krueger collected data from 410 fast-food restaurants near the border between the states of NJ and Pennsylvania (PA) two months before and seven months after the minimum wage increase in NJ. The PA restaurants represent the untreated (control) group, and the NJ restaurants represent the treatment group.

Contemporary research in accounting sometimes uses the term “quasi-natural experiment” (QNE). QNE methods are recognized as the most advisable approach for estimating causal effects rather than estimating “associations” (Bertomeu et al. 2016). The most common QNE methods are difference-in-differences, instrumental variables, and regression discontinuity designs. There is also growing interest in the synthetic control method (SCM) or synthetic difference-in-differences (SDD) (see, e.g., Cunningham (2023, chapter 10) and Arkhangelsky et al. (2021)).

2.4. Difference-in-Differences estimators

DiD method may be applied when the observations in the treatment and control groups move (in time) parallelly. There should be at least two time periods and an event, an exogenous occurrence, an incident, legal change, etc. that happens between those periods.

In the study by Card and Krueger (1994) described above, the outcome variable y_i is employment, and the indicator variable D_i has two values: $D_i = 1$ for the treatment group (i.e., observations for NJ) and $D_i = 0$ for the control group (i.e., observations for PA). There is also the time variable t_i , which represents two periods: $t_i = 1$ and $t_i = 0$ (the minimum wage increase in NJ occurs between these periods), while i is the index of restaurant. The DiD estimator is then the “difference in y for NJ” minus the “difference in y for PA”

$$\beta_1 = [E(y_i | D_i = 1, t_i = 1) - E(y_i | D_i = 1, t_i = 0)]$$

Minus

$$[E(y_i | D_i = 0, t_i = 1) - E(y_i | D_i = 0, t_i = 0)] \quad (7)$$

Another way to obtain β_1 is to estimate the following regression equation:

$$y_i = \beta_0 + \beta_1 D_i \times t_i + \beta_3 D_i + \beta_4 t_i + \varepsilon_i \quad (8)$$

Thus, the DiD estimate of β_1 eliminates the “state effect” β_3 and the “time effect” β_4 .

The key assumption is that, in the absence of treatment, the average change in the response variable would have been the same for the treatment and the control groups. The assumption is termed *parallel trends assumption* because it requires that trends in the y variable in the treatment and the control groups before the treatment be the same. Under such a condition, the DiD-estimator is consistent.

The assumption of parallel trends is untestable. Therefore, to properly apply this methodology, it is essential to perform several sensitivity and robustness tests (Roberts and Whited 2013).

DiD example

Causholi et al. (2022) analyzed the effect of working from home (WFH) on audit quality during the COVID-19 pandemic. The DiD method was applied in the following way. The result variable is the measure of audit quality. They used three such measures: (1) non-reliance restatements (to “capture more egregious misstatements and provide strong evidence of poor audit quality”), (2) unsigned performance-adjusted discretionary accruals (“to detect client firms’ less egregious earnings manipulation”), and (3) auditors’ issuance of going-concern opinions (“represents auditors’ direct communication with financial statement users”). All three audit quality proxies are used “because they have complementary strengths”. The external treatment is an indicator variable equal to one if any local non-pharmaceutical interventions (NPIs) were issued in the county of the audit office between the fiscal year-end and the audit opinion date of the client firm, and zero otherwise. NPIs may be shelter-in-place orders, lockdowns, closures of non-essential services, and school closures. NPIs were recorded in different municipalities in the US during the period March–May 2020. The treatment group is composed of audit engagements affected by county-level NPIs; the control group comprises unaffected audit engagements. The dataset comprises 3,243 observations, of which 857 (26 percent) belong to the treatment group. The general outcome of this study is that WFH has a positive effect on audit quality. Causholi et al. stated that “on average, WFH results in a 1.3 percentage point decrease in the probability of non-reliance restatements, an 11 percent decrease in discretionary accruals, and an 8.1 percentage point increase in the probability of issuing going concern opinions”.

2.5. Regression discontinuity design

Regression discontinuity design (RDD) may be applied in situations in which there is a treatment variable (running variable) X that “decides” that a given observation is treated. Typically, if $X > X_0$, then the observation goes to the treatment group. The threshold (cut-off) X_0 is known. Angrist and Pischke (2015) gave the example that Americans aged 21 and older can drink legally (X variable = age, with the threshold at 21) with the death rate (from all causes) as the y variable. The X variable is the regressor (possibly with other regressors) in a regression model that describes the outcome variable y . The primary idea is that observations that fall just below and just above the cut-off are relatively comparable.

If the probability of treatment goes from 0 to 1 abruptly at the cut-off, the design is called *sharp RDD*. Designs in which the probability of treatment changes discontinuously at the cut-off are called *fuzzy RDD*. An example of sharp RDD might be Medicare enrolment, which happens sharply at age 65, excluding disability situations (Cunningham 2023). In fuzzy designs, passing X_0 increases the probability of treatment, although other variables X may also determine if the observation is treated or not. Generally, for estimating the treatment effect in a sharp RDD case, a single equation regression model is estimated, while more equations are needed for a fuzzy RDD.

One assumption in sharp RDD is local continuity, which ensures that the expected outcome is similar for observations close to but on different sides of the threshold (i.e., in the absence of treatment, the outcomes would be similar). In this regard, Roberts and Whited (2013) mentioned the problem of manipulation: “the ability of subjects to manipulate the forcing variable and, consequently, their assignment to treatment and control groups”. These and other aspects should be considered when designing research that uses RDD.

RDD example

Armstrong et al. (2013) applied the RDD to examine the effects of shareholder support for equity compensation plans on subsequent CEO compensation. The treatment (running) variable X is the percentage of votes for the plan. If the percentage is below the cut-off – typically 50% – then the plan fails. The data they collected show that “there is a clear discontinuity in the distribution of voting outcomes around the 50% threshold”. The dataset comprised equity compensation plans submitted to shareholder vote for US companies between 2000 and 2010. There were 9,520 observations (votes), including 378 “close votes” (i.e., votes between 45% and 55%). RDD was applied to several outcome variables (y) that represent the incentive compensation of CEOs. As a result, Armstrong et al. stated: “we find little evidence that either lower shareholder voting support for, or outright rejection of, proposed equity compensation plans lead to decreases in the level or composition of future CEO incentive-compensation”.

2.6. Limitations

The causal inference methodologies presented here have obvious potential for research in the social sciences. While these methods are being increasingly promoted in contemporary accounting research, there are also compelling arguments that the applicability of causal microeconomic (quasi-experimental) methodologies may be problematic. This may be due to the number of assumptions, limitations, and other obstacles that might lead to unstable outcomes if the research is not correctly performed. One major expectation is replicability. Armstrong et al. (2022) indicated that empirical research results should be reported transparently and be replicable: “without replicability there is no credibility” (see also Hail et al. 2020). Bertomeu et al. (2016) reported on a discussion during the *Causality in the Social Sciences Conference* at Stanford Graduate School of Business in December 2014. Surprisingly, “there was considerable skepticism about statistical techniques commonly referred to as ‘quasi-natural experimental methods’ (Rust 2016), and whether strong, causal inferences typically associated with the use of such methods are reasonable”. Bertomeu et al. mentioned two elements. First, the assumptions for studies should be recognized and clearly stated. Secondly, studies should be rooted in theory. Concentrating only on techniques and data is incorrect.

The remarks about the deficiencies and the reliability of methods presented in the previous subsections remain valid. The survey by Gow et al. (2016) mentioned in section 1 confirms that “making causal inferences requires strong assumptions about the causal relations among variables...; the credibility of these assumptions is rarely explicitly addressed”. Whited et al. (2022) presented a list of good practices in research studies that apply causal inference methodology. Atanasov and Black (2016) propose another checklist to accurately demonstrate causality. They stress that the following points be checked for proper causal reasoning: (1) reverse causation, (2) omitted variable bias, (3) specification error, (4) signaling, (5) simultaneity, (6) the heterogeneous effect, (7) construct validity, (8) measurement error, (9) observation bias, and (10) interdependent effects.

While some of these warnings are common to all statistical-econometric research in finance and accounting, overall, applying causal microeconomic methodology is not an easy task. Various surveys mentioned in this paper (e.g., Armstrong et al. 2022) indicate numerous deficiencies in the papers on causality already published in renowned accounting journals. Therefore, it is advisable that researchers report their findings transparently “across multiple specifications, settings, and methods” (Armstrong et al. 2022).⁵ With many challenges to address,

⁵ Armstrong et al. (2022) indicate that, unfortunately, the incentives for transparency are not greater than the incentives for selective reporting. Various survey papers in social sciences document that “researchers' incentives to find positive results and publish their paper can distort causal inferences - either through selective reporting or ex post justification of research design choices” (Armstrong et al., 2022); see also Ohlson (2023).

accurately applying causal (quasi-experimental) methodologies appears to be very difficult, if not impossible. On the other hand, classical approaches, like regression-type modeling, likewise rely heavily on multiple assumptions. It is the reality of today's research that all accessible techniques are tried more and more often, often without sufficient consideration. This is also the case in finance and accounting research.

3. Illustrations from accounting research

The final section of this review presents examples of causal microeconometrics methods applied in accounting taken from the survey mentioned in Section 1 (Gruszczyński 2022). The survey examined papers published in five leading accounting journals between 2017 and 2021 in selected issues (Gruszczyński 2022, table 2). Of the 246 papers examined, 29 papers (12%) applied causal inference methods. Details of the 29 causal research papers are presented in Table 1.

Table 1. Examples of causal inference published in five leading accounting journals during 2017–2021

| Article | Topic | Data | Causal method |
|----------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|--------------------------------------------|
| "British Accounting Review" | | | |
| Gull et al. (2018) | Female directors vs. Earnings management | French companies 2001–2010 | Propensity score matching |
| Caban-Garcia et al. (2020) | Comparability of disaggregated earnings before vs. After availability of company-disclosed operating cash flow | 15 countries 1995–2004 | Difference-in-differences |
| "Journal of Accounting Research" | | | |
| Bloomfield et al. (2017) | Effect of cross-border migration of accounting professionals relative to other tightly matched professionals before vs. After regulatory harmonization | 33 European countries, including 28 EU member states; LFS statistics, 2002–2010 | Difference-in-differences (double-matched) |

cont. tab. 1

| Article | Topic | Data | Causal method |
|---------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|
| Michels (2017) | Market response for firms required to recognize vs. Firms required to disclose (in a setting in which accounting treatment of an item is exogenously determined) | 78 disclosed subsequent events, and 345 recognized events (US companies 1994–2012, EDGAR base) | Matching: each subsequent event firm matched to a comparable firm that experienced a natural disaster prior to its quarter end |
| Cascino et al. (2019) | Effect of the change in the terms of use (disclosure and regulations) of the online crowdfunding platform Kickstarter introduced on Sept 19, 2014 | Kickstarter data, 255,000 observations, 2009–2017 | Difference-in-differences |
| Ahmed et al. (2020) | Effects of an increase in tick size on financial reporting quality (effects of SEC's 2016 Tick Size Pilot Program) | 9,313 firm-quarters data, April 2015–June 2018 (49% for treated firms, 51% for not treated) | Natural experiment (difference-in-differences) |
| He et al. (2020) | Impact of labor unions on a firm's resource adjustment costs and its degree of cost stickiness | National Labor Relations Board data, 1977–2012; firms where union elections barely pass vs. firms where union elections barely fail | Regression discontinuity design |
| "Journal of Accounting and Economics" | | | |
| Schoenfeld (2017) | Effect of voluntary disclosure on stock liquidity | 368 firms added to the S&P 500 index during 1996–2010 vs. 368 control firms | Propensity score matching; difference-in-differences |
| Erkens et al. (2018) | Effect of adopting clawback provisions on reporting quality and on the probability of CEO turnover: strong clawback adopters vs. Weak clawback adopters | Non-financial firms that adopt a clawback provision, 2007–2013 (4,464 clawback provisions) | Propensity score matching; difference-in-differences |

| Article | Topic | Data | Causal method |
|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------|
| Zhong (2018) | Effect of the mandatory adoption of International Financial Reporting Standards (IFRS) on innovation: adopters vs. Non-adopters | Firm-patent panel data from 12,930 publicly traded firms in 29 countries, 1990–2010 | Difference-in-differences |
| Shan et al. (2019) | Impact of CDS trading on credit protection terms: firms that introduced CDS trading vs. Non-CDS firms | Data on US corporate loans and CDS transactions 1997–2015 | Difference-in-differences |
| DeFond et al. (2020) | Effect of fair value accounting on the association between net income and cash pay following the 2005 adoption of IFRS | 1,654 non-financial firms in 22 countries that mandated IFRS adoption in 2005; three fiscal years prior to adoption vs. the first three fiscal years after adoption | Difference-in-differences |
| Costello et al. (2020) | Changes in loan outcomes for the treatment group relative to the control group; treatment lenders use additional discretion in their decision by adjusting the machine-based recommendation | Data from Credit2B's machine-based scoring model (experiment in November 2018) | Randomized controlled experiment; difference-in-differences |
| Bernard et al. (2021) | Effect of public availability of product market incumbents' financial disclosures on capital structure mimicking of incumbents by entrants | All firms on Amadeus with fiscal years ending 2005–2010 headquartered in France, Germany, Italy, or the UK | Difference-in-differences |
| Dey and White (2021) | Effect of Inevitable Disclosure Doctrine (IDD) on takeover likelihood; IDD decreases knowledge-worker mobility | US data, 28,837 firm-years, 3,117 firms, 1990–2011 | Difference-in-differences |

cont. tab. 1

| Article | Topic | Data | Causal method |
|------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|------------------------------------------------------|
| “European Accounting Review” | | | |
| Chen et al. (2018) | Effect of CEO retirement on conditional accounting conservatism | ExecuComp database, 16,604 observations, 1994–2006 | Propensity score matching |
| Dong and Zhang (2019) | The effect of litigation risk on corporate voluntary disclosure | US data, 1996–2006, firms headquartered in the Ninth Circuit | Propensity score matching; difference-in-differences |
| Sultana et al. (2019) | Effect (on audit fees) of appointment of a new audit committee member with different experience levels to the outgoing member | Australian companies, 13,155 firm-year observations, 2001–2012 | Difference-in-differences |
| Wang et al. (2020) | Effect of corporate governance mechanisms on the quality of integrated reports: e.g., firms that incorporate non-financial Performance measures in executives’ compensation contracts vs. Firms that do not | Integrated reports published in 2012–2015 by 111 companies listed on the Johannesburg Stock Exchange | Propensity score matching |
| Mamun et al. (2021) | Effect of top management counsel (TMC) on stock price crash risk | 13,890 firm-year observations, 2003–2014 (from ExecuComp and CRSP databases) | Propensity score matching |
| “Contemporary Accounting Research” | | | |
| Bronson et al. (2017) | Effect of US cross-listing on audit fees; examined are audit fees for US cross-listed firms vs. US-domiciled firms and foreign non-cross-listed firms | Data for 2000–2011 from COMPUSTAT, Worldscope, and Bank of New York Mellon | Propensity score matching |

| Article | Topic | Data | Causal method |
|------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------|
| Bao et al. (2018) | Effect of voluntary incorporation of clawback provisions in executive officers' compensation contracts on stock price crash risk | Clawback adoption data in the US for 2007–2013: 352 pairs of clawback adopters and non-adopters (Russell 3000 firms) | Propensity score matching; difference-in-differences |
| Goldie et al. (2018) | Influence of perceived auditor quality on investment decisions by bond mutual fund investors | 444 US mutual funds (databases: Morningstar, N-SAR, N-CSR, CSRP) | Propensity score matching |
| da Costa et al. (2020) | Effect of precommitment of upward operating asset revaluation on forecast dispersion, return volatility, and cost of capital | Worldscope data on total assets, earnings, and industry for all listed firms in the UK, 1985–2016 | Propensity score matching |
| Frankel et al. (2020) | Effect of aging-report loan covenants on borrowers' accounts receivable reporting quality; borrowers required to provide aging reports vs. Firms not required to provide aging reports | Loan data from the DealScan database, 1996–2012 | Difference-in-differences |
| Fan et al. (2021) | Effects of corporate governance on earnings management using shareholder-sponsored proposals that pass or fail by a small margin of votes in annual shareholder meetings | RiskMetrics (ISS) data on S&P 1500 companies plus 500 widely held firms in the US, 2003–2015 (final sample of 388 firms) | Regression discontinuity design |
| Ke and Zhang (2021) | Effect of the 2007 public enforcement campaign (enforcement of the first mandatory Corporate Governance Code introduced in 2002) in China | Chinese firms listed on the Shanghai and Shenzhen stock exchanges before campaign 2004–2006 vs. after 2008–2010 | Propensity score matching |

cont. tab. 1

| Article | Topic | Data | Causal method |
|--------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|---------------------------|
| Ma et al. (2021) | Effect of CEO's general skills on credit risk of firm's overall creditworthiness, firms that hire generalist ceos vs. Firms that hire specialist ceos | BoardEx and Compustat data for 1,272 US firms, 1992–2015. | Propensity score matching |
| Tang et al. (2021) | Effect of managerial labor market mobility on managers' use of expectation management to lower analyst expectations to achievable levels | Data from I/B/E/S. Compact Disclosure, COMPUSTAT and CRSP; 1994–2013; 95,689 firm-quarter observations | Difference-in-differences |

Source: author's own elaboration.

As stated in Section 1, of the 246 papers considered in the survey of leading journals, 165 papers were based on some type of financial microeconomic methodology (Gruszczyński, 2022). The 29 papers presented in Table 1 above constitute nearly 18% of all the microeconomic papers examined.

Conclusion

Regression-based statistical-econometric methodology in accounting research is rarely able to show causal relationships. Methods termed quasi-experimental or causal microeconomic provide a better base for finding evidence of causality. However, the assumptions of the causal framework may not be fulfilled, and errors in properly applying causal methods may occur in practice. This methodological field is relatively young and still developing into a more mature form.

It should be noted that regression models, especially panel regression models prevailing in current accounting applications, are legitimate tools for finding common associations as well as attempting to show suggestions of causal relationships. Still, causal microeconomics methodologies appear to be the appropriate tools for verifying causal effects.

This paper presented selected methods of causal microeconomics with examples from the accounting literature. It also discussed issues concerning the applications of this methodology. The upward trend of quasi-experimental methods that appear in leading accounting journals has been evidenced in several surveys. Despite various obstacles, it seems that this trend will continue and, therefore, researchers in accounting need to be aware of its merits and deficiencies.

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