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# Support behind the scenes: the relationship between acknowledgement, coauthor, and citation in Nobel articles

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## Abstract
Acknowledging individuals in research articles is known to be a personal and private expression of appreciation compared to other types of acknowledgment, such as financial support. Early studies have demonstrated the significant relationship between acknowledgement, coauthor, and citation. Little did we know to what extent of these relationships and which prompt what to some degree among them. We adopt a series of multivariate analyses, Bayes' theorem, statistical analysis, and "before and after" matched-group studies to illustrate the acknowledgement patterns in 6323 research articles of 196 Nobel Prize laureates (NPL) from 2008 to 2018. Acknowledgment is consistently proved to significantly relate to co-authorship and citation where co-authorship and citing have an approximately 10% increasing effect on acknowledgement behavior. Our study is the first to state the order of such triangle: acknowledgement is significantly ahead of co-authorship and arguably occurs before citing behavior. Moreover, acknowledgement strengthens more than half of NPL on their co-authorship for 11% and citation for 72% after they acknowledge others. We verify the substantive possibility of co-authorship and citing behavior from acknowledgement and introduce a formation of a new norm of scholarly communication. This will greatly contribute to the matter of evaluation metrics and social network detection.

**Keywords** Acknowledgement · Coauthor · Citation · Reward system · Scholarly communication

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## Introduction

It has been found that many reviewers and committees take great pleasure in reading candidates' acknowledgements once they begin the dissertation review process. This response likely stems from not only the candidates' expressions of gratitude but also genuine curiosity to see who the candidates will thank (Hyland, 2003). Readers may wonder who top scientists in the world, such as Nobel Prize laureates, would thank in their articles. Unlike certain types of award acceptance speeches (Condit, 2018), acknowledgements in research articles are arguably more personal, singular, or private expressions of appreciation and contribution (Giles & Councill, 2004). Since acknowledgements became a routine part of the rhetorical structure of academic writing, they have played an important role in scholarly communication (Cronin, 2001).

Acknowledgements reflect a wide range of support, including moral, financial, editorial, presentational, instrumental/technical, and conceptual support (Cronin et al., 2003). With the development of indexing technology for metadata repositories, bibliometricians, funding agents, and others have conducted substantial studies on acknowledgement patterns (Cronin & Overfelt, 1994; McCain, 1991), especially as these reveal funding distributions (Álvarez-Bornstein & Montesi, 2021; Hubbard & Laddusaw, 2020). Furthermore, due to the diverse content found in acknowledgements sections, researchers have been interested in methodological studies on extracting context from acknowledgements (Song et al., 2020). These efforts aim to illustrate the reward system from the perspective of acknowledgement information. The importance of the reward system in the scientific community is well understood as the three behaviors in the reward triangle—acknowledgement, authorship, and citation—combine to drive knowledge creation and public advocacy. However, studies on the reward system have not equally emphasized these three behaviors; authorship, citation, and their interrelationship have long proved useful as well-known quantitative methods across research areas (Díaz-Faes & Bordons, 2017). Regarding the relationship between acknowledgement and the other two behaviors, previous studies have predominantly relied on funding analysis in combination with acknowledgement analysis. Although recent researchers have shed light on individuals as objects of acknowledgement statements (Paul-Hus et al., 2017a; Tian et al., 2021), further in-depth work is needed to address one central research question: what are the exact relationships between the three behaviors in the reward system? In parallel, two subordinate and progressive questions will be discussed:

(1) How is acknowledgement precisely related to (co)authorship and citation? Do (co)authorship and citation have any impact on acknowledgement, and if so, to what extent? Are there differences across research fields?
(2) Can acknowledgement prompt (co)authorship and/or citation, or vice versa? To what extent?

To achieve these goals, we have selected disambiguated Nobel articles with acknowledgement information as our dataset. Undoubtedly, the Nobel prize is the most prestigious and influential award in science. The data on their work has been widely used to study major questions in scholarly communication, including collaboration (Chan et al., 2015), citation impact (Garfield & Welljams-Dorof, 1992), and the reward system in science (Shen & Barabási, 2014). This data provides not only a proxy to analyze elite scientists but also a reliable and high-quality data source for understanding the reward system in science. Due to the unparalleled influence of Nobel laureates, they may be more selective in their choice of collaborators and be more cautious in using their social capital in the reward system (Wagner et al., 2015). The social capital of Nobel laureates is also more impactful than non-Nobel laureates. Nobel Prizes do not only have positive effects on the citation impact of the laureates but may also induce a chain reaction in the neighboring citation network (Frandsen & Nicolaisen, 2013). Therefore, the effects of acknowledgement on citation and co-authorship can be captured more effectively, and their relationships can be understood more precisely from the Nobel data compared to non-Nobel data. After giving a primary overview of our data sample, our first focus is on the acknowledgement trends within the time segments of individual award years. We then conduct a multivariate analysis to refine the factors of co-authorship and citation as they affect acknowledgement. Only if it can be proved that acknowledgement has been affected by co-authorship/citation can we move forward to address such matters as effect size, correlations, and sequence. The follow-up sections illustrate the co-authorship/citation pattern before and after acknowledgement from three dimensions, including each Nobel Prize laureate, each pair, and each acknowledgee; these aim to reveal the degree of the impact.

This research offers an important contribution to scholarly communication studies by integrating considerations of correlation and descriptive analysis on the reward triangle. Our research verifies that co-authorship and citation can also be implicitly tackled, as in previous acknowledgements. Therefore, acknowledgements can be considered as another means of tracking co-authorship and citation behavior. The findings further a long-lasting research agenda around the genesis of collaboration and citation behavior and the formation of a new norm of scholarly communication.

## Related work

### Acknowledgement patterns

Acknowledgements have been present in monographs since the sixteenth and seventeenth centuries (Roberts, 2003). It was not until the 1940s that acknowledgements started appearing in journal articles (Bazerman, 1988), and few studies on their origin until the 1990s, when Cronin initiated a new era of acknowledgement research (Cronin, 1991; Cronin & Overfelt, 1994; Cronin & Weaver, 1995; Cronin et al., 1993). Since then, studies on acknowledgements have been used to answer a variety of questions involving the research reward system. This research trend has drawn increasing attention from scholars seeking to identify the different acknowledgement patterns. Cronin (1991) identified six acknowledgement categories: paymaster, moral support, dogsbody, technical, prime mover, and trusted assessor. Hyland (2003) likewise proposed six main categories: academic support, access to data, moral support, clerical services, financial resources, and technical help. Other scholars presented different types of categories based on the different venues they sampled (McCain, 1991; Rattan, 2013; Tiew et al., 2002). Song et al. (2020) summarized all these categories into the most common eight types: access, peer interactive communication, moral, technical, clerical, financial, manuscript and editorial, and unclassifiable support. Although acknowledgement is often considered as the "good" gesture, Baccini and Petrovich (2022) explained the possible strategic intentions and distinguished the normative from the strategic acknowledgements.

### Access to acknowledgement information

These taxonomies have guided further analysis of acknowledgement behaviors, serving various purposes such as the use of a publication's acknowledgements for bibliometric and evaluation purposes. The issue of accessing acknowledgement data emerged early on, and the collection of such data became a focus of scholars' attention and research. In 1998, the Wellcome Trust's Research Outcome Database (ROD) was developed, which contains funding data extracted from the acknowledgements sections of publications by year and field. This database enables researchers to extract information about funding sources from acknowledgements on a larger scale (Lewison, 1998) and evaluate impact using citation indicators (Lewison & Dawson, 1998; Lewison et al., 2001). Since August 2008, the Web of Science (WoS) has indexed funding agencies and, if available, grant numbers, giving subsequent research on the act of acknowledgement a chance to flourish, even though limitations have been noted at various times (Paul-Hus et al., 2016; Tang et al., 2017; Zhao et al., 2018).

### Acknowledgement analysis

Financial support has also caught the attention of bibliometricians, database suppliers, and stakeholders that acknowledgement analysis is often synonymous with funding analysis from several aspects. The relationships between funding and research performance of individual and institutions are the most widely encountered topics (Győrffy et al., 2020; Rigby, 2011). For instance, researchers have used WoS funding information to study the funding sources (governmental or private) of cancer research in Russia (Markusova et al., 2012), in Europe (Begum et al., 2018), and in different domains (Álvarez-Bornstein & Bordons, 2021; Paul-Hus et al., 2017a) under different language backgrounds (Díaz-Faes & Bordons, 2014). Needless to say, funding has been upheld as one of the most important engines driving increases in publications and citations (Zhao et al., 2018). Although significant variations have been observed among different countries (Wang et al., 2012), the diversity of recognized funding sources is positively correlated with the total citation count and citation percentile (Gök et al., 2016). However, studies on other types of acknowledgement behavior are limited by access to data; as a result, only recently have scholars given attention to acknowledgements directed towards individuals. For instance, Paul-Hus has investigated acknowledgement behaviors deeply, ranging from individual acknowledgees to institutional supports (Desrochers et al., 2018; Paul-Hus et al., 2016, 2017a, 2017b) However, with the aid of information extraction techniques (Giles & Councill, 2004), network analysis (Petrovich, 2022; Rose & Georg, 2021), and machine learning technologies (Song et al., 2020), scholars are able to automatically gather in-depth and large-scale acknowledgement data to study who gets acknowledged and what factors are involved.

### The reward triangle

Acknowledgements, along with citations and authorship, constitute the "reward triangle" (Cronin & Weaver, 1995; Díaz-Faes & Bordons, 2017), suggesting the importance of acknowledgements as an essential norm in scholarly communication. One of the first intentions of the science of science community was to shed light on the relationships between acknowledgements, authorship, and citations. Yet the early literature failed to carry out this program for reasons outlined above. Obviously, citations and authorship are the cornerstones for assessing the development of science and individual researchers. Exploring their interplay has been an ongoing trend across different research units, such as countries (Henriksen, 2018), institutions, domains (Newman, 2004), and individuals (Frandsen & Nicolaisen, 2013). Even well-known indicators only include these two behaviors (Hirsch, 2005). Nevertheless, studies examining the relationships within the reward triangle mainly focus on either the dynamism exclusively between citations and authorship or on funding as a proxy for acknowledgement. Studies on the relationships between the three behaviors spread sporadically. Alongside the work of Paul-Hus and others, two recent studies by Tian et al. (2021) explored the relationship between the acknowledgement network and citation count, and Rose and Georg (2021) explored the acknowledgement and collaboration. They established that the acknowledgement network plays a moderating role on the collaboration network and is strongly connected to citation count. Their study represents a valuable starting point, but further consolidation of datasets could have allowed for a more comprehensive exploration.

## NPLs' research performance

Nobel Prize laureates (NPLs) are the top experts in the science community. Along with their contributions to human society, their careers and accomplishments are widely publicized. Although concerns about the Nobel Prize system are raised from time to time (Casadevall & Fang, 2013; Polemis & Stengos, 2022), researchers persist in investigating all aspects of the Nobel Prize, such as laureates' personalities (Lebuda & Karwowski, 2021), their contributions to individual fields (Hansson et al., 2020), and the contributions the Nobel Prize makes to science (Zhai et al., 2016). Most relevant to our paper are the studies on NPLs' research performance. Previous researchers have taken genuine interest in understanding the trajectory of becoming an NPL, resulting in three main types of research performance studies. Predicting NPL status has always been an uptrend in our society, with predictors ranging from Eugene Garfield (Garfield & Malin, 1968) to junior researchers early in their career (Baffes & Vamvakidis, 2011). Apart from this, researchers tie laureates' success to coauthor and citation networks, such as their collaboration patterns (Chan et al., 2015; Wagner et al., 2015), citation timeline (Bjork et al., 2014), and research focus (Sebastian & Chen, 2021). Moreover, the reasons a researcher becomes an NPL are of interest in the form of either pre- and post-Nobel Prize comparisons (Chan et al., 2014, 2018) or comparisons with non-NPLs (Yan et al., 2020). Based on bibliometric data and quantitative methods, research has shown NPLs' trajectories to be similar to those of normal researchers (Gingras & Wallace, 2010; Li et al., 2019b). Among all the topics surrounding the Nobel Prize, who and how NPLs thank in their research articles has yet to be discussed.

To the best of our knowledge, a comprehensive quantitative understanding of the relationships within the reward triangle has not yet been achieved. We are still far from systematically understanding how and why authors acknowledge others based on bibliometric data. Thus, we here apply multivariate analysis and before-and-after matched-group study to investigate the relationships among acknowledgement, co-authorship, and citation.

## Research design

### Theoretical considerations

On top of that acknowledgement has been proved to be related to citation and collaboration network (Tian et al., 2021), our present work focuses on how exact this relation depicts, specially illustrating the possible sequences of the occurrences of acknowledgement, co-authorship, and citation. The motivations of acknowledgement, co-authorship, and citation are quite complicated and have been stated in many different types of summaries. Besides the aforementioned reasons of acknowledgement, it is important to highlight the distinctiveness of citation and collaboration. Garfield's classic work (1964) on citation behavior has evolved over the years. Wang et al. (2018) reviewed literature and concluded five types of citation motivation: related research topics, accessibility of literatures, reputations of journals and authors, social alignment like ideology and cultural background, and individual factors of the citing author. Regarding collaboration, Bozeman and Corley (2004) summarized ten reasons followed by a strong emphasis of informal conversation: including access to expertise, access to equipment or resources one does not have, to encourage cross-fertilization across disciplines, to improve access to funds, to obtain prestige or visibility, to learn tacit knowledge about a technique, to pool knowledge for tackling large and complex problems, to enhance productivity, to educate a student, increasing specialization of science, and for fun and pleasure.

To better distinguish the homophily of the motivations of acknowledgement, co-authorship, and citation, we herein integrated and compared all the aforementioned reasons to address the phenomenological matter of the reward triangle. Among the three behaviors, authorship is commonly considered as the strongest in providing legitimacy to scientists (Díaz-Faes & Bordons, 2017). Authors should be fully linked to public responsibility for research contents (Rennie, 2000). Therefore, adding and being added a co-author for a research article should be taken very seriously, even most seriously compared to acknowledgement and citation. Secondly, acknowledgement offers a unique writing section that authors can express in formal and informal communication. Comparing with acknowledgement, citation not only reflects the impact on another's research but requires to be represented quite formally (Desrochers et al., 2017). As a result, the nature of acknowledgement, co-authorship, and citation has led to different levels of strictness in their usage, with acknowledgement being the most flexible and co-authorship being the most stringent. This corresponds with a pioneer understanding decades ago that acknowledgement section can be recognized as a source of sub-authorship collaboration (Patel, 1973).

These theoretical findings not only enhance our understanding of the scopes and similarities of reward triangle but also raise the idea of how exactly the three behaviors occur in a researcher's career trajectory or during a research project. The strictness of usage gives us a possible sequence of occurrence of three behavior, i.e., acknowledgement, citation, and co-authorship. The reality can be rather complicated due to the similarities according to the aforementioned motivations. For instance, in a single article, acknowledging one's supervisor for their guidance may occur simultaneously with citing their paper. Moreover, acknowledgement and co-authorship can be exclusive from one another in the same paper. Nevertheless, both the theoretical basis and the enumerated summaries warrant validation through quantitative analysis. Thus, we attempt to illustrate the sequence of the three behaviors.

## Data sampling

Our study requires highly precision on disambiguated name information. Therefore, we choose a well-curated dataset (Li et al., 2019a) to ensure disambiguated publications of NPL to minimize precision lose from name extraction in the following steps. We collected 520 NPLs' names in three fields, Chemistry, Physics, and Physiology or Medicine (hereafter: Medicine), from the official Nobel Prize website. 93,934 publications stored in Li's dataset were downloaded to match with the DOIs in WoS publication metadata, where we can obtain the acknowledgement information by batch. 7172 out of the 12,615 matched publications (2008–2018) were identified due to the insufficiency of acknowledgement information in WoS before 2008. After 649 distinct articles were excluded because they had more than 50 coauthors, 6323 distinct publications were finalized as our sample, representing 196 NPLs.

The identification process comprises three steps. First, to identify and extract personal names from the acknowledgements, we utilized the Named Entity Recognition function (NER) in Stanza, a Python natural language analysis package. This process allowed us to obtain the cohorts of acknowledgees.

The second step involved mapping the names in the three cohorts: acknowledgees, coauthors, and cited authors. The latter two cohorts were extracted from the publication metadata of WoS. It is important to note that cited authors were determined based on the indexing limitation of WoS, where they correspond to the first authors listed in the references. In order to align with these names' format from WoS, we transformed the names in the acknowledgees and coauthors cohorts into the format of "last name, initial letter of given name."

Finally, we performed a fuzzy matching strategy to preliminarily map the names under a rule that required the full surname and the first letter of the given name to be exactly the same. This matching process aimed to establish initial connections between the cohorts of acknowledgees, coauthors, and cited authors.

Third step is to assure the accuracy of the mapping results, we manually extracted 30 random publications in each field (90 in total) to calculate extraction precision and recall. Precision is the ratio of correct extractions to the sum of redundant, lost, incorrect, and correct extractions; recall is the machine's correct extractions divided by the manual correct extractions. Given an average of 85.10% precision (86.81% in Chemistry, 86.00% in Physics, and 82.48% in Medicine) and an average of 95.61% recall (99.07% in Chemistry, 93.01% in Physics, and 94.74% in Medicine), we estimate that the NER performs well. We compile the acknowledgees, coauthors, and first reference authors (WoS metadata only provide the first author in references) as a whole for further analysis in Table 1.

## Indicators and variables

We introduce the following indicators to illustrate the effects among the three behaviors. Acknowledgee: Personal names which appear in NPL article acknowledgements. Coauthor: NPL's coauthors in our final dataset. Cited: First author of each reference in each Nobel article. In the following analysis, we collectively call these three behavior receivers as Supporters.

We believe acknowledgement is an independent behavior in drafting an article, i.e., acknowledging one person does not influence acknowledgement of another in the same

**Table 1** Summary of data sample

| Field | | Chemistry | Medicine | Physics | Total frequency | Total distinct items |
|---|---|---|---|---|---|---|
| # Publications | | 2646 | 2336 | 1341 | 6519 | 6323 |
| # Persons | NPL | 68 | 68 | 60 | 196 | 196 |
| | Acknowledgee | 4772 | 6227 | 2623 | 13,622 | 11,734 |
| | Coauthor | 7294 | 9579 | 4971 | 21,844 | 19,524 |
| | Cited | 67,241 | 65,571 | 25,819 | 158,631 | 113,760 |
| Circumstances | Acknowledge only | 3695 (40.32) | 4968 (54.21) | 1879 (20.5) | 10,542 (100) | 9165 (115) |
| # Persons (%) | | 63 (92.65) | 63 (92.65) | 51 (85) | 177 (90.31) | 177 (90.31) |
| # NPL (% total NPL) | | M = 58.65 | M = 78.86 | M = 36.84 | M = 59.56 | M = 51.78 |
| Average per NPL | Coauthor only | 4172 (34.07) | 6082 (49.67) | 2770 (22.62) | 13,024 (100) | 12,245 (106) |
| | | 66 (97.06) | 67 (98.53) | 55 (91.67) | 188 (95.92) | 188 (95.92) |
| | | M = 63.21 | M = 90.78 | M = 50.36 | M = 69.28 | M = 65.13 |
| | Cite only | 64,008 (58.46) | 62,059 (56.68) | 23,437 (21.4) | 149,504 (100) | 109,495 (137) |
| | | 68 (100) | 68 (100) | 60 (100) | 196 (100) | 196 (100) |
| | | M = 941.29 | M = 912.63 | M = 390.62 | M = 762.78 | M = 558.65 |
| | Acknowledge and coauthor | 700 (37.49) | 848 (45.42) | 416 (22.28) | 1964 (100) | 1867 (105) |
| | | 45 (66.18) | 50 (73.53) | 27 (45) | 122 (62.24) | 122 (62.24) |
| | | M = 15.56 | M = 16.96 | M = 15.41 | M = 16.1 | M = 15.3 |
| | Acknowledge and cite | 811 (39.07) | 863 (41.57) | 597 (28.76) | 2271 (100) | 2076 (109) |
| | | 52 (76.47) | 55 (80.88) | 40 (66.67) | 147 (75) | 147 (75) |
| | | M = 15.6 | M = 15.69 | M = 14.93 | M = 15.45 | M = 14.12 |
| | Coauthor and cite | 2856 (39.77) | 3101 (43.18) | 2054 (28.6) | 8011 (100) | 7181 (112) |
| | | 66 (97.06) | 68 (100) | 57 (95) | 191 (97.45) | 191 (97.45) |
| | | M = 43.27 | M = 45.6 | M = 36.04 | M = 41.94 | M = 37.6 |
| | Acknowledge, coauthor, and cite | 434 (39.53) | 452 (41.17) | 269 (24.5) | 1155 (100) | 1098 (105) |
| | | 38 (55.88) | 47 (69.12) | 22 (36.67) | 107 (54.59) | 107 (54.59) |
| | | M = 11.42 | M = 9.62 | M = 12.23 | M = 10.79 | M = 10.26 |

and/or other articles. Therefore, in our multivariate analysis, we consider acknowledgement as an event involving only within two people. Thirteen indicators were calculated only under the circumstances of a pair, i.e., a combination of an NPL and an acknowledgee.

1. Total acknowledgement count: total number of times the NPL has acknowledged a peer.
2. Years with acknowledgement: number of years the NPL has acknowledged a peer.
3. Total co-authorship count/cites: total number of times the NPL has coauthored/cited a peer.
4. Years with coauthoring/citing: number of years the NPL has coauthored/cited a peer.
5. Duration from first time acknowledge to coauthor/cite: duration from first time an NP acknowledges a peer to first time she/he coauthor with or cite, or vice versa if acknowledgement appear after coauthor/cite.
6. Average duration from NP to co-authorship/cite: total duration from winning NP to coauthor/ citation year divided by (4).
7. Average duration from NP to acknowledge: total duration from winning NP to acknowledgement year divided by (2).
8. Given NPL's total coauthors/cites: total number of coauthors/cited authors for this given NPL. Log transformed.
9. Given NPL's total acknowledgees: total number of distinct acknowledgees for this given NPL. Log transformed.
10. Given NPL's total publication: total number of publications for this given NPL. Log transformed.
11. is_loyal_supporter: a binary value to identify if a peer has been acknowledged by only one NPL. Interacting with (3) (8) (9) to identify the intensity of the relationship of a pair.
12. Two dummy variables to distinguish the field differences (Chan et al., 2015): is_Chemistry and is_Medicine, the field that NPL was awarded.

In selecting variables for the models, we first consider (1) (2) as dependent variables. Indicators (3) (4) are the treatment variables, which are commonly used as indicators in scientometrics (Wang et al., 2018; Zhao et al., 2018). The average value of the four is not included because it is derived from these two variables, especially average value has been stated as misleading variable in factor estimation (Farys & Wolbring, 2017). Other indicators are control variables. (5)–(7) are to test the impact from time because time periodish (e.g., age, time gap) is often intertwined in research performance (Liu et al., 2018). (8)–(10) are selected to measure from the viewpoint of where a pair stands among all pairs involving an individual NPL, i.e., the importance of a given pair to an NPL among all pairs this NPL has (Lou et al., 2018).

## Analysis methods

This study aims to reveal the acknowledgement patterns, presenting by two indicators: *Total acknowledgement count* represents the strength of that an NPL acknowledges a peer. *Years with acknowledgement* indicates the frequency of such acknowledgment. Both of them are typical cases of count data: they can only take non-negative integer values and clearly follow a disproportional distribution (Fig. 1). Therefore, Poisson and negative binomial regressions (NBR) are preferable for modeling count data. We test the differences

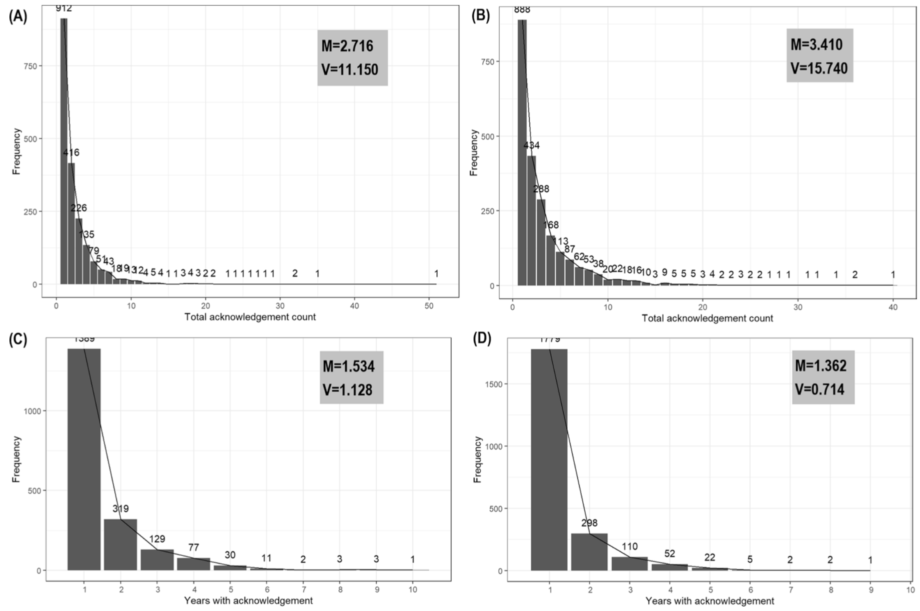


**Fig. 1** Total acknowledgement count histograms (**A** coauthor, **B** cite) and Years with acknowledgement histograms to observe dispersion (**C** coauthor, **D** cite)

between mean (M) and variance (V) and select NBR for modeling *total acknowledgment count* due to the unequal *M* and *V* of the acknowledgement counts in Fig. 1A and B, and select Poisson regression for modeling *years with acknowledgment* as the non-significant difference between *M* and *V* in Fig. 1C and D. Since Poisson distribution is a special case of negative binomial distribution, we model both as NBR model first: the relationship between the count data of a pair $Y^t_{nk}$ of NPL $n$ and acknowledgee $k$ in a collection of given year $t$, the treatment indicators for the coauthor/cite factors $F^t_{nk}$ and the control variables $C^t_{nk}$ as follows:

$$\mathrm{P}\left(\mathrm{Y} = y^t_{nk}\right) = \begin{pmatrix} \frac{1}{a} + y^t_{nk} - 1 \\ \frac{1}{a} - 1 \end{pmatrix} \left(\frac{a\mu^t_{nk}}{1 + a\mu^t_{nk}}\right)^{y^t_{nk}} \left(\frac{1}{1 + a\mu^t_{nk}}\right)^{\frac{1}{a}} \tag{1}$$

with

$$\mu^t_{nk} = e^{C^t_{nk}\beta + F^t_{nk}\gamma + u^t_{nk}} \tag{2}$$

The parameter $\mu^t_{nk}$ represents the expected mean number of *total acknowledgement count* or *years with acknowledgement E(Y)*. The parameter $u^t_{nk}$ represents a random error term that is assumed to follow a standard normal distribution:$u^t_{nk} \sim N(0, \theta^2)$. The dispersion parameter $a$ allows the mean and variance of $Y$ to differ. The NBR model thus reduces to a Poisson regression when we model *years with acknowledgement*, which is the case that $a$ approaches zero. To minimize confounding effects, we compose the model into two groups, i.e., with and without control variables. Due to the endogeneity of coauthor-based and cite count variables, within these two groups, we gradually test the significances of four independent variables: *total co-authorship count/cites* and *years with coauthoring/citing*.

To address the sequence of the three behaviors, we calculate the occurrence probabilities for each NPL in a given year to compare these two circumstances, i.e., "acknowledgement ahead of coauthor" vs. "coauthor ahead of acknowledgement" and "acknowledgement ahead of citation" vs. "citation ahead of acknowledgement." Bayes' theorem is a proper model to measure the probability of co-authorship/citation with a priori probability of acknowledgement. However, acknowledgement and co-authorship/citation are independent events in actual life. We combine the correlation coefficient (*Coe*), which will be tested in multivariate analysis and correlation analysis, in the Bayesian model to relate the behaviors. Equation (3) shows that the probability of $A$ after $n$ years given that $B$ occurs in year $t$ is the product of the probability $A$ occurs in year $t+n$ and the probability $B$ occurs in year $t$ with their correlation coefficient.

$$P\left(A_{t+n}|B_t\right) = Coe(A,B) \times P(A_{t+n} \cap B_t)/P(B_t) = Coe(A,B) \times \frac{A_{t+n}}{\sum_0^{t+n} A_t + \sum_0^t B_t} \times \frac{B_t}{\sum_0^t B_t} \tag{3}$$

We can simplify the probability calculation to a case that an NPL chooses the acknowledgee, the coauthor, and the cited in a certain order. The logic of selecting any of the three in turn is similar with random sampling in statistical experiment if considering an academic network of an NPL is composed of these three types of authors. The probability of an NPL picking a random acknowledgee $y$ in year $t$ $P\left(y_t\right)$ is the reciprocal of the total new acknowledgees from the initial year *0* to year *t*.

$$P\left(y_t\right) = \sum_0^t \left(\frac{1}{\sum_N y_t}\right) \tag{4}$$

In the sequence analysis section, we choose the most active years for all three types of supporters (2009 and 2011) for most NPLs ($M=145$, 70.73%) as examples to compare the differences (Sig) between the probabilities of acknowledgement in 2009 and co-authorship/citation in 2011 and the probabilities of co-authorship/citation in 2009 and acknowledgement in 2011.

$$Sig(P\left(Coauthor_{2011}|Acknowledge_{2009}\right), P\left(Acknowledge_{2011}|Coauthor_{2009}\right)) \tag{5}$$

$$Sig(P\left(Cite_{2011}|Acknowledge_{2009}\right), P\left(Acknowledge_{2011}|Cite_{2009}\right)) \tag{6}$$

Due to the significant difference in variance between citation count and the count of acknowledgement and co-authorship, we used averages to normalize these three types of supporters into the range from 0 to 1. The average value is calculated as that the new supporters in one behavior in a certain year divided by the total supporters in the same year and same behavior; this value will be applied to the probability calculation. However, to this end, the initial year—for most NPLs, 2008—is much misleadingly calculated as 1 because our data sample starts in 2008. We manually set the probability of each type in the initial year as 0.5 as it is the mean of the range of the probability. It also results from that the probability of an NPL to choose a specific supporter for acknowledging before and after is 0.5.

To assess statistical significance, we apply the Chow test to identify structural breaks in the time sequence, the Spearman correlation test for the relationships between the indicators, and the *t*-test and Wilcoxon test for paired samples to ensure the significance of the difference between pre- and post-acknowledgement.

## Findings

### Overview

Table 1 gives an overview of the data. In total, we collected 6323 publications from 196 NPLs who acknowledged 11,734 peers, coauthored with 19,524 peers, and cited 113,760 peers. Of the three fields we examined, Chemistry includes the largest number of publications (2646 from 68 NPLs), with 2336 publications from 68 NPLs in Medicine and 1341 publications from 60 NPLs in Physics. The smaller sample in Physics results from the fact that 644 articles were excluded due to their very high co-authorship. As for the scale of the three behaviors, apparently, NPLs in Medicine prefer to acknowledge (6227, M = 91.57) and coauthor (9579, M = 140.87) with peers the most, while NPLs in Chemistry cited the largest number of authors (67,241, M = 988.84).

We divide the total sample into seven circumstances according to the intersection of the three behaviors. All seven circumstances are present within all fields, which, needless to say, is normal in research articles. Every NPL has cited others; however, not all of the NPLs' articles rely on coauthors (95.92%) and acknowledgees (90.31%). What interests us is that because of the unequal sample in Physics, the values in Physics are smaller than in the other two fields under five of the seven circumstances, i.e., all but "acknowledge & coauthor" and "acknowledge & cite." In other words, the values in Physics are only comparable to the rest in these two circumstances. This ensures the validity of our samples in the following analysis. Moreover, 1098 pairs represent a combination of all three behaviors. These pairs can in fact be considered as special cases of "acknowledge & coauthor" and "acknowledge & cite," where they have been included during the summary. Therefore, 1964 "acknowledge & coauthor" pairs and 2271 "acknowledge & cite" pairs are chosen as the analytic sample in the following sections.

### Descriptive analysis of acknowledgement trends

In this section we report the distributions of annual new acknowledgees pre- and post-Nobel Prize. We selected those NPLs who won the Nobel Prize from 2008 to 2018, resulting in a total of 53 NPLs in our dataset. The reason to truncate NPLs from 2008 is to coordinate with the publication years (2008–2018) in our dataset. The analysis of new acknowledgees are highly possible related to NPLs' productivities, especially the cumulative publications of each NPL. We limited the publication time to align with their conferral time to reduce the effect from cumulative number of publications. We use scatter plots with embedded line plots of confidence interval (CI) to visualize the distributions of new acknowledgees for NPLs as well as the distributions in the three fields (Fig. 2). The NPLs have acknowledged, on average, ten new peers every year. Our results identify a positive trend in new acknowledgees in the period before the Nobel Prize, which changes abruptly after conferral, with yearly values fluctuating around the value observed at the time of the award (shown within 95% CI). For these figures, because the exact time of the potential breakpoint (the award year) is known, we use the Chow test to identify a structural break—that is, a strong enough shift between the pre- and the post-award acknowledgement

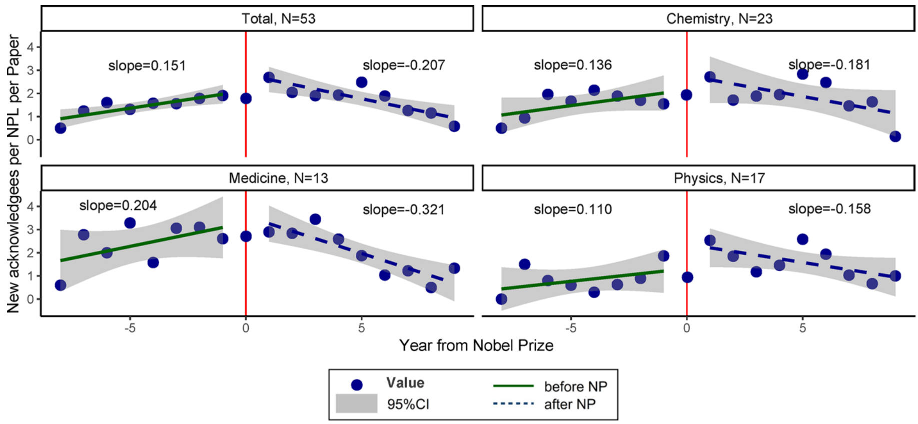


**Fig. 2** Differences in acknowledgement before and after Nobel Prize conferral since 2008

pattern. All test results confirmed significant differences between pre- and post- award periods, both overall and in each field. Given that we also observe an inverted U-shaped relation between the number of new acknowledgees and laureate age, we consider the Nobel Prize winning year a highly appreciative year for all NPLs. This phenomenon is coincidentally in line with earlier research that claims a similar pattern for NPLs in terms of new co-authorship (Chan et al., 2015). In addition, the dots are widely scattered pre-award but more predictable post-award, indicating that after receiving their prize, NPLs have somehow established the acknowledgement pattern they will persist in, notwithstanding the common decrease. The trend in the number of new acknowledgees pre- and post-award also varies slightly between fields. Specifically, the pre-award growth rate in Physics is the slowest (0.110), while that of Medicine is the fastest (0.204). Post-award shows the same comparison between fields, the trend in Physics shows the slowest decline (–0.158); in Medicine, it decreases fastest (–0.321).

## Multivariate analysis on effects of co-authorship/citation on acknowledgement

Table 2 shows the results from one out of four groups of models (All the results in the Supplementary Information). We have not combined co-authorship and citation together into the model because the relationship between citation and co-authorship, which has been widely discussed is endogenous for modeling the relationship separately between acknowledgement and co-authorship or citation. The intercepts of all the models indicate a significant increase in the number of acknowledgements and in the surrounding co-authorship or cite counts. Now we look into each group of models.

When estimating the effects of *years with coauthoring* and *total co-authorship count* on *total acknowledgment count* and *years with acknowledgement*, the results resemble into three features (1) coauthor-based variables have effects on acknowledgement count, (2) the effects are separately significant, however, (3) *total co-authorship count* does not show significance if the model involves *years with acknowledgement* (Model 3). The effect sizes of *years with acknowledgement* increase if the model involves the former one (Model 3). Apparently, coauthor-based variables will give a 11–12% of increase on acknowledgement count and years. The impacts increase to almost 20% given control variables. The effects

**Table 2** Results summary of multivariate analysis (Dependent variable is total acknowledgement count with coauthor-based independent variables)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| (Intercept) | .992 *** | .997 *** | .992 *** | .834 *** | .808 *** | .808 *** |
| | (.020) | (.020) | (.020) | (.048) | (.047) | (.047) |
| Years with coauthoring | .120 *** | | .157 *** | | .196 *** | .195 *** |
| | (.019) | | (.030) | | (.020) | (.030) |
| Total co-authorship count | | .079 *** | − .052 | | | .001 |
| | | (.018) | (.031) | | | (.030) |
| Duration from first time acknowledge to coauthor | | | | .150 *** | .213 *** | .213 *** |
| | | | | (.020) | (.021) | (.021) |
| Avg. duration from NP to co-authorship | | | | − .004 | .003 | .003 |
| | | | | (.022) | (.022) | (.022) |
| Avg. duration from NP to acknowledge | | | | − .103 *** | − .097 *** | − .098 *** |
| | | | | (.020) | (.020) | (.020) |
| Given NPL's total coauthors | | | | .164 *** | .182 *** | .182 *** |
| | | | | (.039) | (.038) | (.039) |
| Given NPL's total acknowledgees | | | | − .167 *** | − .160 *** | − .160 *** |
| | | | | (.044) | (.044) | (.044) |
| Given NPL's total pub | | | | .029 | − .018 | − .019 |
| | | | | (.039) | (.039) | (.040) |
| Is_loyal_supporter | | | | .024 | .018 | .018 |
| | | | | (.069) | (.068) | (.068) |
| Is_Chemistry | | | | .249 *** | .267 *** | .267 *** |
| | | | | (.058) | (.057) | (.058) |
| Is_Medicine | | | | .108 | .115 * | .115 * |
| | | | | (.057) | (.056) | (.056) |
| AIC | 8159.940 | 8183.054 | 8159.404 | 8074.468 | 7986.870 | 7988.868 |
| BIC | 8176.688 | 8199.802 | 8181.735 | 8135.878 | 8053.862 | 8061.443 |

Exponentiated coefficients; *t* statistics in parentheses. $N = 1964$. All continuous predictors are mean-centered and scaled by 1 standard deviation. *** < 0.001, ** < 0.01, * < 0.05

of most control variables change variously when we add *years with coauthoring* (Model 4 vs 5). But comparing Model 5 and 6, almost all the control variables are unaffected by this change in terms of either significance or effect size. Resemblances appear on the effects on *years with acknowledgement*. This indicates that comparing to total amount of coauthor count, *years with coauthoring* on behalf of the co-authorship frequency influences collaboration stronger. In terms of fields differences, we compare Physicists to other two field scientists. Coauthor-based variables have significantly different effects on *total acknowledgment count* between Physicists and others. But the effects on *years with acknowledgment* between Chemists and Physicists are, on the contrary, similar. Given these evidences, Physicists focus less on the intensity of collaboration than other scientists, and medical scientists tend to value the frequency of collaboration more than others.

As for cite count variables, some similarities are shown in the SI. *Total cite count* has less significantly effect on acknowledgment than *years with citing*. Both Model 1 in citation results indicate that *years with citing* increases 12% of acknowledgment values, pointing in the direction of a substantial chain effect. Similarly, it will increase 10% given an increase in the number of citing years, a weaker but still positive effect. Similar to the coauthor-based results, adding control variables to the models strengthens the effect size of *years with citing* (Model 1 vs 5), and adding *total cite count* decreases the effect of it (Model 5 vs 6). For field differences, medical scientists show significant differences from others in terms of either *total acknowledgment count* or *years with acknowledgement*.

To sum up, *years with coauthoring, total cite count,* and *years with citing* are the three most significant factors affecting acknowledgement count among other coauthor-based and cite count variables. Correlation tests show the same results. *Total acknowledgement count* is weakly but significantly related to *years with coauthoring* (0.134, $p<0.001$), which is higher than that of *total co-authorship count* (0.133, $p<0.001$), and *years with citing* (0.136, $p<0.001$), which is higher than that of *total cite count* (0.132, $p<0.001$). To gain a comprehensive view, we can consider these as indicators of how often the NPLs interact with others. *Years with coauthoring* represents the length of collaboration, and *years with citing* and *total cite count* indicates the strength of recognition. An example may help in comparing total values and *years with coauthoring*: coauthoring ten papers with a peer in an only single year and coauthoring with her/him once a year for ten years give the same totals, but the latter is a more convincing evidence of a long-lasting collaboration.

## Acknowledgement before and after co-authorship/citation

Having obtained significant relationships between acknowledgement and co-authorship/citation, we can investigate whether acknowledgement promotes co-authorship and cite count. This case can be converted into a matter of probability, which is calculated from the data for the three behaviors (taking 2011 as an example) and the correlation coefficients given by correlation analysis. Since both *years with coauthoring* and *years with citing* are significant from regressions, we apply their correlation coefficients (0.134, 0.136) to Eqs. (3) and (4) to calculate the probability. Only 91 NPLs (46.43%) meet the criteria of publishing every year from 2008 to 2011 with new supporters in all three behaviors. The differences in Eqs. (5) and (6) are tested by the Wilcoxon paired test, which indicates a significant difference for co-authorship ($F=2.591$) and a null effect for citation. In Fig. 3, dots in the upper triangle can be read as an NPL co-authorship/citation after acknowledgement, and dots in the lower triangle represent co-authorship/citation before acknowledgement. More than half of the acknowledgements occur before co-authorship (68.13%) and citation

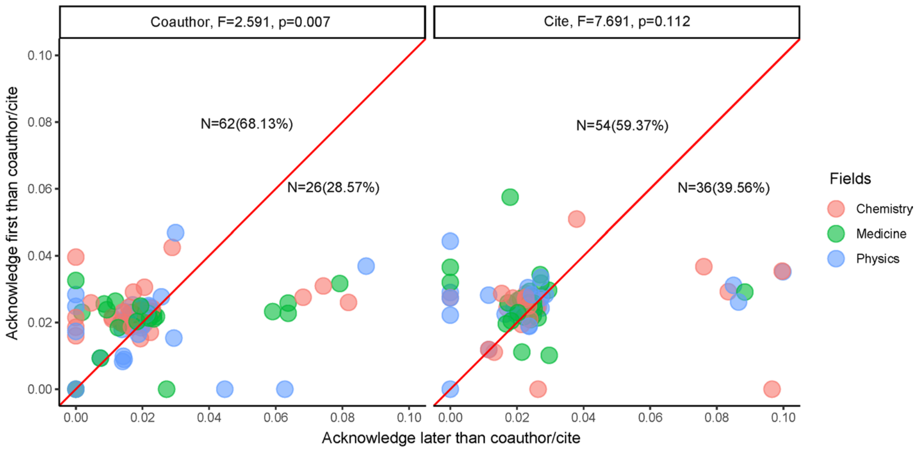


**Fig. 3** Probability of acknowledging before and after co-authorship/citation for individual NPL in 2011 ($N=91$)

(59.37%). Therefore, it indicates that acknowledgements have a subsequent guiding effect on co-authorship and citation: previous acknowledgees are likely to be NPLs' coauthors later on. To investigate the differences between fields, we illustrate the dots in different colors. For NPLs in 2011, it seems no statistically significant differences among different fields.

If it is possible for acknowledgees to be NPLs' coauthors after they are acknowledged, it would be interesting to see how long it takes to become coauthors. In Fig. 4, the dots represent the total acknowledgement count in a year for all given NPLs. The $x$-axis is calculated as the period from the first time an NPL acknowledges a supporter until they coauthor with or cite that same supporter. Welch's one-way ANOVA tests show there are no statistically significant differences among different fields nor between co-authorship and citation. The test results indicate that NPL acknowledgement of supporters follows a general pattern: the time at which NPLs coauthor with or cite an author is evenly distributed at the time they acknowledge the author for the first time because every box in the Fig. 4 is evenly tied, and the frequency of NPLs citing supporters is higher than that of NPLs coauthoring with them. Although about 20% of NPLs have coauthored with or cited supporters in the same year they acknowledge them, the T test results showed significant differences between the time differences and 0 in all four cases ($p<0.001$), i.e., acknowledgement and coauthor/cite do not occur in the same year. In Physics, NPLs coauthor/cite supporters two years after acknowledging them which is relatively later than that in other fields. However, it takes less time than in other fields for physicists to coauthor with or be cited by an NPL when they are acknowledged one to four years prior.

In Fig. 5, we look deeply into the pre- and post-acknowledgement preferences of NPLs from the perspective of each pair and each NPL. The percentages are calculated by dividing the total co-authorship/cite counts before and after acknowledgement by the total co-authorship/cite count occupied by a pair or an NPL. Dots in the upper triangle indicate that a pair or an NPL coauthor with or cite others more often before acknowledgement. Conversely, dots in the lower triangle represent a pair or an NPL coauthor with or cite others more often after acknowledgement. Unlike the probability in Figs. 3 and 5 gives the degree to which acknowledgement strengthens co-authorship and citation. In other words,

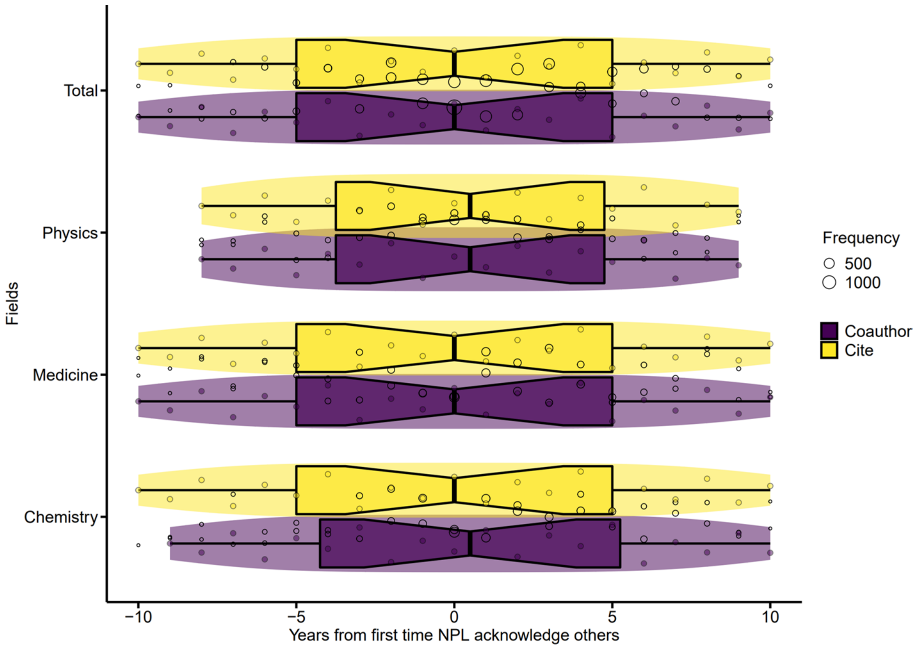


**Fig. 4** Time differences from first time NPL acknowledge others to co-authorship/citation

we can answer the question of what percent of co-authorship and citation collaboration occurs before and after acknowledgement.

In both figures in Fig. 5, Wilcoxon paired tests show significant differences between pre- and post-acknowledgement behavior for both co-authorship and citation. The F value shows the effect of the statistical differences. It implies that acknowledgement boosts co-authorship by 3.8% and cite count by 33.1% for each pair, and by 11.5 and 72% respectively for each NPL. Apparently, around half of the pairs build up coauthor (48.73%) and citation (51.48%) relationships after acknowledgement, and over half of the NPLs coauthor with (60.66%) and cite (69.39%) others after acknowledgement. Both of the results in the after-acknowledgement groups exceed, and even double, those in the before groups, indicating that more than 60% of co-authorships and citations were completed after acknowledgement. These results substantively address the correlated effect of acknowledgement on co-authorship and especially on citation. For NPLs in different fields, it is interesting to see that physicists are consistently different from other two groups of scientists. Compared to medical scientists and chemists, a proper proportion of physicists tend to coauthor with and cite their peers before acknowledgement rather than after acknowledgement (See Fig. 5B).

We now turn to the dynamic changes in the types of NPL supporters. First, we classify supporters into two groups: "Before," meaning an NPL would prefer to coauthor with or cite this supporter before acknowledging them, and "After," indicating the reverse. To quantitatively distinguish these two groups, we calculate the frequency differences for a supporter and her/his paired NPL. If a supporter coauthored or was cited in more years before than after her/his NPL acknowledged her/him, this supporter is defined as a "Before" person; otherwise, she/he is an "After" person. Those supporters with equal numbers of before and after years are excluded in this section, meaning that 566 (28.82%) pairs in the coauthor set and 669 (29.46%) pairs in the cited set are not included in Fig. 6.

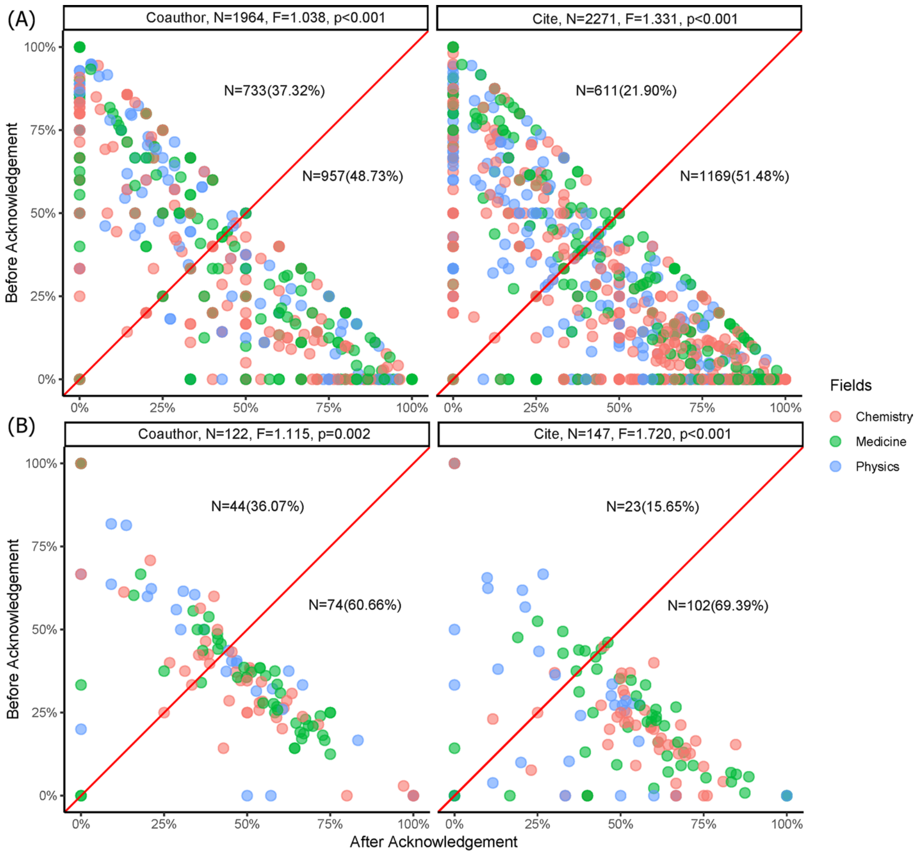


**Fig. 5** Coauthor/cite percentages for each pair (**A**) and NPL (**B**) before and after the NPL acknowledges others

Wilcoxon paired tests show that there is a statistically significant difference between the cited authors' distributions before and after acknowledgement, but the coauthors' differences are not significant.

We visualize the dynamic differences in Fig. 6. To mitigate the issue of scale noise,, we used the average number of supporters as the y-axis, representing the average number of supporters in years that the supporters appear before or after acknowledgement. The two reversed U-shaped lines in Fig. 6A and B form a double-hump-shaped distribution. The lines and the gaps between them exhibit distinct trends in the two distributions. Consistent with the statistical tests results, the two lines for co-authorship in Fig. 6A bear a closer resemblance to each other than the two lines for cited authors in Fig. 6B. Several common features are evident in both figures. First, there are more supporters classified as "After" than "Before.". Secondly, there are more "Before" persons before NPLs acknowledge them for the first time than "Before" persons after getting acknowledged. The differences between the two lines in each figure consistently range from one to two acknowledgees. Two major differences between the co-authorship and citation distributions are: the peaks for "After" persons are different, and the gap between lines for cited authors in the positive $x$-axis is larger than that for coauthors. These results reinforce the observation that NPLs

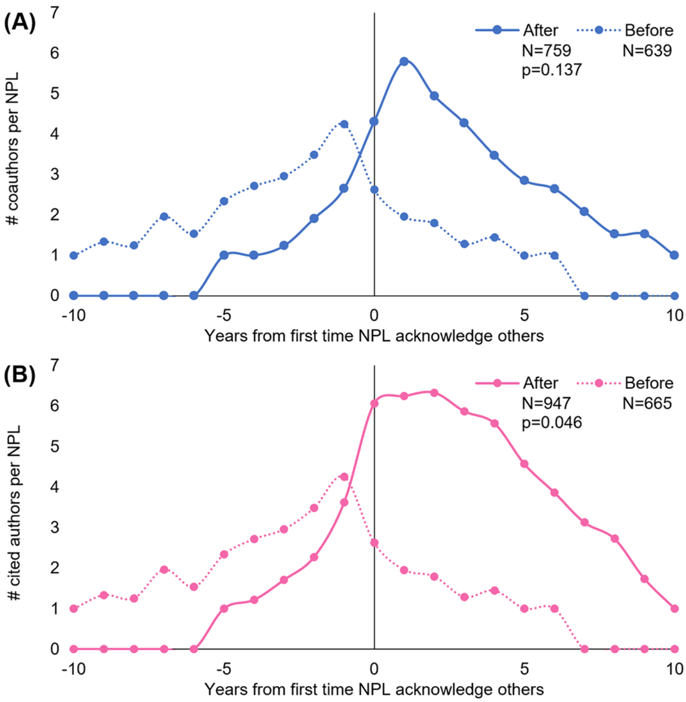


**Fig. 6** Types of coauthors (**A**) and cited authors (**B**) before and after NPLs acknowledge them

coauthor with/cite more peers after they acknowledge them than before. The stability of citing others a few years after acknowledgement indicates a possibility that NPLs consistently cite their acknowledgees two to three years after acknowledgement.

## Discussion and conclusions

Acknowledgement plays key roles in composing research articles across all fields, yet our understanding of how and whom authors acknowledge is limited. To address this gap, we extracted more than 10,000 individual acknowledgees from over 6000 Nobel articles from a sample of 196 Nobel Prize laureates in three fields—Chemistry, Physics, and Physiology and Medicine—to understand how they acknowledge others and to identify acknowledgement patterns in relation to co-authorship and citation. Several major findings are established in this study.

Solid evidence shows that acknowledgement is significantly related to co-authorship and citations. These results corroborate the work of Cronin and Weaver (1995), Desrochers et al. (2018), and Díaz-Faes and Bordons (2017) regarding the connection between the three. These researchers have clearly demonstrated the concept of the connections. Our study further clarifies that co-authorship and citation are moderately related to acknowledgement and have an approximately 10% effect on acknowledgement likelihood. We did not expect this effect to be any stronger than the current results since acknowledgement, after all, cannot directly affect coauthor/citation choices. Through multivariate analysis, we found that acknowledgement can be affected by the number of years in which coauthoring/citing takes place and by total cite count, but not by the average citation count. Apart from the explanation of the importance of long-lasting collaboration, this methodological reflection corresponds with the work of Farys and Wolbring (2017) who advise against simply using the average number of citations in causal effect estimation.

Second, our attempt is the first to demonstrate the order of the reward triangle. Introducing a Bayesian-based probability to measure the sequence of the three behaviors, we found that the relationships between them can be more precisely represented than the Venn diagram suggested by Díaz-Faes and Bordons (2017). Acknowledgement is significantly ahead of co-authorship and arguably occurs before citing behavior. The main aim of this article was to make a theoretical contribution on how acknowledgement is situated in scholarly communication in relation to co-authorship and citation. Aforementioned earlier research established the existence of the relationships, leaving open the question of the trajectory by which the relationships are built up. One possible explanation of this pattern is that co-authorship is a debatable commitment among the authors, which requires more substantial contributions for research (Ponomariov & Boardman, 2016) than acknowledgement requires. Building up a coauthor relationship takes more time, while acknowledgement is more flexible. Thus, co-authorship is not necessarily "following" acknowledgement but is generally slower to appear than acknowledgement.

In the meantime, acknowledgement can be seen as "super-citation" (Edge, 1979), a special occasion of citing behavior, which makes it difficult to distinguish which occurs first. Even though numerous previous studies have successfully achieved their research goals by solely relying on first-author-indexed references from WoS, it is important to acknowledge the potential impact and limitations of this approach (Larivière et al., 2013; Nederhof et al., 2010). However, in the context of this particular study, the analysis of citing behavior was hindered by the indexing limitation of authors in the references from WoS. Regrettably, this restricted the total population of cited authors within the sample, potentially affecting the ability to accurately determine the timing of acknowledgment before or after citing for an NPL.

Relaying on the above, the third finding is that acknowledgement strengthens co-authorship and citation to a large degree. Over half of the individuals in our dataset obtained an increasing connection after acknowledgement, indicating that acknowledgement exerts a positive effect on the collaborative ambiance in scholarly communication. After all, acknowledgement is always a gesture of appreciation. Moreover, the dynamic changes in new supporters before and after Nobel Prize conferral suggest that the most appreciative year for NPLs is the award year, which can be a swoop-in opportunity to be acknowledged by NPLs for the rest of us.

Our study captured a new norm in the reward triangle for the scholarly communication community. Conditionally, we encourage technological improvements in metadata indexing for database developers. Although this article focuses on analyzing only NPLs, who may differ from regular researchers, the metadata in Nobel articles, which we acquired from a disambiguated dataset, is not fully comprehensive. The lack of acknowledgement information restricted us to a ten-year period, and the inconsistencies in indexing items necessitated manual verification. We have minimized errors from sampling by deducting over-authored papers and manually disambiguating acknowledgees' names. These adjustments have not significantly altered the results but have improved their precision and reliability. In future studies, we will specifically explore the exceptions and the reasons behind them, such as pairs who acknowledge after co-authoring and those who cite less after acknowledgement.

Another potential following-up research is to focus on the causal analysis of co-authorship and citation motivation, which have always caught attention of researchers in scientometrics community (Min et al., 2021). Yet the causal effect of them affected by acknowledgement maintains mysterious. Our present study shed lights on the possible reason to co-authorship and citation that might be from acknowledgement. However, more information of NPL and their peers will be needed for a causal analysis to control the confounders, such as academic age, career trajectories, geographical distances, and more (Liang et al., 2020). Retrieving this information poses challenges, but one possible method to conduct a matched group analysis by comparing the pairs who have acknowledged before co-authorship/citation with those who have not, and the pairs who have acknowledged before co-authorship/citation with those who acknowledged afterwards. This method would provide a more precise presentation of the causal effect.

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