THE IMPACT OF THE NOBEL PRIZE ON THE LEVEL AND DIRECTION OF INNOVATION*

BANG DINH NGUYEN§

ABSTRACT. This paper examines how the Nobel Prize shapes the level and direction of innovation, drawing on a unique dataset of 466 Nobel laureates and 1,876 nominees in Physics, Chemistry, and Medicine throughout the 20th century. Leveraging the 50-year confidentiality rule on nominations, I implement a dynamic difference-in-differences design that compares innovation in winners' fields with those of non-winning nominees. The analysis reveals a significant post-award increase in patenting within the patent classes of Nobel laureates, as well as spillovers into adjacent fields with a temporal lag. The surge in patenting is mirrored by an increase in publications whose titles and abstracts contain the same n-grams as prize-winning papers. These findings suggest that the Nobel Prize not only boosts innovation in the awarded topics but also fosters broader scientific exploration over time.

Keywords: Nobel Prize, science, innovation

JEL classification: N70, O31

Date: August 31, 2025. Please click here for the latest version.
§University of Bayreuth. Email: bang.nguyen@uni-bayreuth.de.
*I would like to thank Ho Fai Chan and Benno Torgler for sharing the data on other awards received by the Nobel laureates. I am also grateful to Kenny Kahuma and Luis Schroeder for excellent research assistance.

1. Introduction

The Nobel Prize is the most prestigious and influential award of the modern era. While the number of scientific prizes has roughly doubled every 25 years since 1900 (Ma and Uzzi, 2018), none rival the Nobel Prize's combination of prestige, monetary value, subject range, and century-long legacy. Since its inception in 1901, 349 Nobel Prizes have been awarded to 653 laureates in Physics, Chemistry, and Medicine. Prior research has examined how the Prize shapes the careers of laureates (Zuckerman, 1967; Jones, 2010; Weinberg and Galenson, 2019; Ham and Weinberg, 2019; Li et al., 2020) and their socioeconomic and educational backgrounds (Chan and Torgler, 2015; Li et al., 2021; Novosad et al., 2024). Much less is known, however, about how the Nobel Prize affects innovation itself, specifically, what happens to scientific research and publication patterns after a field receives a Nobel. Understanding how the Nobel Prize affects innovation is fundamental for designing policies that promote impactful research and advance global health and social welfare.

This paper investigates whether the Nobel Prize concentrates innovation in the winning topics or spreads it across diverse scientific areas. At the outset, it is not obvious whether the Nobel Prize boosts or suppresses research activity in the awarded fields. On the one hand, Nobel laureates may attract more researchers to their fields due to increased media exposure, greater visibility at conferences, enhanced funding prospects, and the prestige associated with working on a Nobel-recognized topic. On the other hand, scientists may shift toward non-winning fields, perceiving winning areas as saturated or already mature, and instead pursue novel opportunities elsewhere. If the Nobel Prize does indeed steer the direction of scientific inquiry, its influence may carry unintended consequences. For instance, when a Nobel Prize rewarded the discovery of insulin, it may have put a brake on research for the cure of diabetes.

To address this question, I exploit two unique features of the Nobel Prize selection process and construct a novel dataset linking Nobel nominees and laureates to their U.S. patenting and publication records. First, winning the Nobel prize is inherently unpredictable: there are many deserving discoveries to choose from, yet a maximum of only three winners are selected each year. This creates a quasi-random allocation of prestige across comparable discoveries. Second, under the statutes of the Nobel Foundation, the names of the nominees and related information remain confidential 50 years after the award. As of 2025, the nomination database includes entries from 1901 to 1974 for Chemistry and Physics, and up to 1953 for Medicine. I link 466 Nobel laureates and 1,876 non-winning nominees to their U.S. patent records in Google Patents and publications

in Microsoft Academic Graph, and analyze the subsequent impact on patenting activity across technology classes and publication trends in leading field-specific journals.

My empirical strategy implements a staggered difference-in-differences design, exploiting the quasi-random timing of awards and the confidentiality of nominations. This approach identifies causal effects by comparing changes in innovation between the research topics of laureates and those of similarly distinguished but unrewarded nominees. I validate the two key identifying assumptions: (1) no anticipation (winning the Nobel Prize is not predictable based on observable technology characteristics), and (2) parallel trends (pre-award trends in innovation are similar between fields of laureates and non-winning nominees). For patents, I define technological fields using the U.S. Patent Classification (USPC). To measure scientific output, I also use publication data from the Microsoft Academic Graph, restricting the analysis to the top 200 journals in each field. To trace the diffusion of scientific ideas, I analyze the evolution of publications containing the same bigrams (e.g., paramagnetic anisotropy) and trigrams (e.g., nuclear magnetic moment) as those found in Nobel-winning papers, exploiting the dataset on n-grams compiled by Arts et al. (2025).

The results reveal a significant post-award increase in both patenting and citations within the technological fields associated with Nobel laureates. On average, winning patent classes experience an increase of 49 patents and 475 citations per patent class per year following the award, relative to the classes linked to the non-winning nominees. Adjacent patent classes also exhibit a delayed but noticeable rise in innovation activity. These patterns are mirrored in the scientific literature, with a rise in publications whose titles and abstracts contain the same n-grams as those found in Nobel-winning papers. Overall, the findings suggest that the Nobel Prize not only intensifies innovation in awarded areas but also acts as a catalyst for broader scientific exploration.

What drives the increase in innovation in Nobel-recognized fields? I examine two potential mechanisms regarding public funding and inventor dynamics. Using data from Fleming et al. (2019) on government-funded research, I find that the number of government-funded patents does not increase more in Nobel-related classes compared to those of non-winning nominees. Instead, the growth is driven primarily by privately funded patents. An analysis of inventor dynamics reveals an increase in the number of inventors active in Nobel fields, with nearly 80% of them being new entrants—those patenting in these fields for the first time.

The results are robust. The point estimates and statistical significance remain consistent across different estimators, model specifications, transformation of the dependent variables, and sample

restrictions. The findings are also insensitive to alternative definitions of technological fields and different rankings for top journals. I perform several diagnostic tests to address concerns related to staggered difference-in-differences designs, including tests for the influence of negative weights and for the sensitivity of estimates to potential violations of the parallel trends assumption.

This paper makes several contributions. First, it advances our understanding of how prizes affect innovation. While much attention has been devoted to inducement prizes—those that reward future achievements based on predefined goals, far less is known about the effects of recognition prizes, which reward past accomplishments. Several studies have documented strong field-shaping effects of such recognition prizes (Brunt et al., 2012; Burstein and Murray, 2016; Nicholas, 2013; Moser and Nicholas, 2013). Jin et al. (2021) conduct a large-scale analysis of over 400 scientific prizes and find that prizes significantly increase the number of publications, citations, and participation by both new entrants and established researchers in prize-winning topics. However, prizes have become increasingly concentrated among a small group of scientists and ideas in recent decades (Ma and Uzzi, 2018), raising concerns about negative spillover effects on the broader allocation of scientific attention (Reschke et al., 2018). Unlike previous studies that rely on comparing winning to non-winning fields using propensity score matching to construct counterfactuals, this paper offers a cleaner identification strategy by comparing winning fields directly to those of equally prominent but non-winning nominees.

Second, this research contributes to the extensive literature on how scientists choose their research topics. Scholars have identified various factors influencing these decisions. The visibility and impact of prominent scientists, or superstars, can attract others to particular research areas, while gatekeepers—those who control access to key resources or publication venues—may steer the direction of scientific inquiry. For example, Azoulay et al. (2010) show that the death of superstars can significantly alter the flow of talent and ideas within a field. Funding availability also plays a central role in shaping research agendas. Myers (2020) highlights how targeted grants and shifts in funding priorities can incentivize scientists to pursue certain topics over others, sometimes leading to rapid growth in emerging fields or, conversely, the neglect of underfunded areas. Borjas and Doran (2012) provide evidence that talent inflows—such as those driven by international migration—can foster both collaboration and competition, thereby influencing topic selection and innovation. Exposure to new ideas through collaboration, conferences, or institutional environments further expands the scope of scientific inquiry. Bell et al. (2018) and Truffa and Wong (2025) show that interaction with

diverse peers and interdisciplinary networks can stimulate interest in novel topics, promote knowledge exchange, and encourage the pursuit of unconventional research questions. This paper adds to this literature by examining how recognition through the Nobel Prize influences these dynamics.

Third, this paper contributes to the growing body of work on the Nobel Prize itself. Novosad et al. (2024) document that Nobel laureates are disproportionately drawn from privileged socioeconomic backgrounds; for example, their fathers rank, on average, in the 87th percentile for income and the 90th percentile for education. Other studies examine the effects of Nobel recognition on post-award citations and career trajectories (Babutsidze and McCabe, 2024; Ham and Weinberg, 2019; Weinberg and Galenson, 2019), the timing of peak creativity (Jones, 2010; Jones and Weinberg, 2011), and the lag between discovery and recognition (Mitsis, 2022). This paper complements these studies by shifting the focus from individual laureates to their broader scientific fields, identifying prestige-based recognition as a powerful yet underexplored driver of innovation dynamics.[1]

Finally, this research also connects to the broader literature on how major historical and institutional forces shape U.S. innovation. Prior work has studied the effects of wartime science policy—such as compulsory licensing following World War I (Moser and Voena, 2012), the creation of the Office of Scientific Research and Development during World War II (Gross and Sampat, 2023), and the recruitment of scientists from Nazi Germany through the Operation Paperclip (Moser and Nguyen, 2025). In addition, high skilled immigrants have been shown to exert a profound and long-lasting impact on U.S. innovation (Hunt and Gauthier-Loiselle, 2010; Moser et al., 2014). While this literature focuses on external policy or demographic shocks, my paper shifts the focus inward—toward the internal dynamics of the scientific system. In doing so, it identifies prestige-based recognition as a distinct and influential through which innovation is shaped.

Overall, my findings suggest that while the Nobel Prize can catalyze innovation in winning fields, it may also steer scientific attention away from equally deserving areas. This highlights a broader tension: competition among researchers is a powerful driver of innovation, yet the structure of recognition—when highly selective—can unintentionally distort the allocation of scientific effort. The implication for science policy is not to reduce competition, which fosters excellence, but to broaden the set of prestigious awards that recognize high-impact research. In recent years, the proliferation of scientific prizes, such as the Breakthrough Prize, the Kavli Prize, and field-specific

[1] A study by Congressional Research Service (1986) finds that hosting Nobel laureates is most strongly correlated with citations to scientific literature—an indicator of research quality—and much less so with the quantity of financial or human resources or with technological performance.

awards, reflects a shift toward this more inclusive recognition model. Expanding the ecosystem of scientific awards may help sustain the benefits of competitive science while mitigating the risks of overly concentrated attention on a narrow set of topics.

The remainder of this paper is structured as follows. Section 2 provides an overview of the Nobel Prize, with a focus on the nomination and selection process. Section 3 describes the data used in the analysis. Section 4 outlines the empirical strategy. Sections 5 and 6 present the results on patents and publications, respectively. Section 7 concludes.

2. Background

2.1. **Origin of the Nobel Prize.** The Nobel Prizes are prestigious international awards administered by the Nobel Foundation. They were first awarded in 1901, marking the fifth anniversary of Alfred Nobel's death. The original prizes recognized achievements in five fields: Physics, Chemistry, Physiology or Medicine, Literature, and Peace. A sixth prize, in Economic Sciences, was established in 1968 by Sveriges Riksbank in memory of Alfred Nobel.

The prizes are funded by Alfred Nobel's personal fortune, as stipulated in his will. Each recipient, known as a laureate, receives a diploma, a green gold medal plated with 24-karat gold, and a monetary award. In his will, Nobel specified that the prizes should be awarded "to those who, during the preceding year, have conferred the greatest benefit to humankind." More specifically, the prizes in Physics, Chemistry, and Medicine were to be awarded to three individuals "who made the most important discovery or invention in the field of physics, [...] the most important chemical discovery or improvement, [...] the most important discovery within the domain of physiology or medicine."

Although Nobel intended the prizes to recognize work from the previous year[2] and to be awarded to a single person, the criteria have evolved over time. Today, prizes in each field are often shared by up to three individuals to reflect the collaborative nature of modern research. Furthermore, awards frequently honor work conducted years or even decades earlier, acknowledging the time required for scientific validation.

[2]The *Statutes of the Nobel Foundation* make it clear that older works can also be considered for the prize "if their significance has not become apparent until recently." This implies there is no formal time limit for considering a discovery. However, in the early decades, this so-called recency rule was interpreted more narrowly, and only work conducted within the preceding two decades was typically eligible (Hargittai, 2002, p.12).

2.2. **Nomination Process.** The Nobel Prizes in Physics and Chemistry are awarded by the Royal Swedish Academy of Sciences, while the prize in Physiology or Medicine is awarded by the Nobel Assembly at Karolinska Institute in Stockholm. These institutions have dedicated Nobel Committees that handle the preparatory work involved in the adjudication of each prize (The Nobel Foundation, 2001, p.25). In September of the year preceding the award, the Nobel Committees send individual invitations to selected university professors, scholars, and experts worldwide. Invitees are chosen to ensure broad representation across countries and institutions.

Nominations must be submitted to the respective Committees by February 1 of the award year. Members of the awarding institutions and previous Nobel laureates can also propose candidates. However, self-nominations are strictly prohibited. A complete list of eligible nominators and a timeline of the nomination process are provided in Appendix B and Figure B1, respectively.

Secrecy is a crucial aspect of the Nobel nomination process (Hargittai, 2002, p.23). The invitation letter contains a firm warning: "You should treat your invitation and nomination as highly confidential and should not discuss them." The Committees emphasize that they are interested in the nominator's personal judgment, not the consensus of any collective body. This confidentiality is designed to protect nominators from external pressure by potential nominees and their associates.

2.3. **Selection Process.** Once the nominations are received, each Committee investigates the candidates with the assistance of specially appointed experts. After thorough review, the Committees make their selections and submit their recommendations to the prize-awarding institutions. A final vote is then taken, typically in October, and the Nobel laureates are announced immediately afterward.

While the precise procedures vary slightly across Committees, all aim to fulfill Alfred Nobel's intention: to award those who have "conferred the greatest benefit to humankind." Importantly, Nobel's will makes clear that the prize is intended to reward great discoveries, not necessarily great scientists. The prize is meant to recognize specific achievements, not lifetime accomplishments, and important discoveries are not always made by the most prominent or authoritative figures in a field (Hargittai, 2002, p. 49). A well-known example is Albert Einstein, who did not receive the Nobel Prize for his best-known contributions to physics—the theories of special and general relativity. Instead, he was awarded the prize "for his services to theoretical physics, and especially for his discovery of the law of the photoelectric effect."

2.4. **Confidentiality Rule.** According to the Statutes of the Nobel Foundation, all nomination-related materials—including the names of nominees and nominators, as well as evaluations and expert opinions—must remain confidential for at least 50 years. This restriction helps preserve the integrity and independence of the selection process. Statute §10 of the Nobel Foundation states:

> Proposals received for the award of a prize, and investigations and opinions concerning the award of a prize, may not be divulged. A prize-awarding body may, however, after due consideration in each individual case, permit access to material which formed the basis for the evaluation and decision concerning a prize, for purposes of research in intellectual history. Such permission may not, however, be granted until at least 50 years have elapsed after the date on which the decision in question was made.

For prizes awarded more than 50 years ago, the nomination archives may include information on both the nominators and the nominees. In some cases, however, the records remain sealed as long as the individuals mentioned are still alive.

3. Data

3.1. **Nobel Prize Laureates and Nominees.** Throughout the 20th century, 277 Nobel Prizes were awarded to 466 laureates in Physics, Chemistry, and Medicine.[3] The Nobel nomination archive contains records of candidates nominated for these prizes since their inception in 1901. However, due to the 50-year confidentiality rule, only materials older than 50 years are currently accessible.

The data used in this study include 1,876 non-winning nominees[4] in Physics and Chemistry from 1901 to 1974, and in Medicine up to 1953. For each nomination entry, the archive records the nominee's name, gender, year of birth and death, year of nomination, and the name and institutional affiliation of the nominator.

As an illustrative example, Edwin Herbert Land (1909–1991), co-founder of the Polaroid Corportation and known for his contributions to polarized light, photography and color vision, received six nominations but never won a Nobel Prize. He was nominated three times in Physics: in 1954 by Harlow Shapley (Harvard), in 1973 by Karl Helmer Gustavson (Stockholm), and in 1974 by Robert

[3]Notably, three individuals have received the Nobel Prize twice: Marie Curie was awarded the prize in Physics (1903) and Chemistry (1911); John Bardeen won twice in Physics (1956 and 1972); Frederick Sanger won twice in Chemistry (1958 and 1980).

[4]The nomination archive shows that nominations for corporations or organizations are exceptionally rare. In Physics, only one informal collective—"Nuclear scientists" (nominated in 1946 and 1947)—and one organization, CERN (nominated in 1970), have ever been nominated. In Chemistry, just one company, Geigy SA, was nominated, in 1947.

Burns B Woodward (Cambridge), who won the Nobel Prize in Chemistry in 1965. Land was also nominated three times in Chemistry: in 1972, 1973, and 1974 by George Porter (London), who won the Nobel Prize in Chemistry in 1967.

See the Table 1 for a summary of Nobel laureates and nominees. On average, winners receive 5.59 nominations in their winning year, whereas non-winning nominees receives and average of 1.51 nominations. The distribution of nominations among non-winners is highly left-skewed, as many nominees received only a single nomination. Based on both the ratio of winners to nominees and the share of nominations awarded to winners, the Nobel Prize in Medicine appears to have had the most intense competition, while Physics and Chemistry exhibit similar levels of competitiveness.

Table 1. Summary of Nobel Laureates and Nominees

	Physics	**Chemistry**	**Medicine**	**Total**
Nobel laureates				
Total (1901–2000)	161	133	172	466
Laureates with nomination data	100	85	63	248
Nominations	5.73	5.27	5.79	5.59
Cumulative nominations	13.36	13.19	8.44	11.50
Non-winning nominees				
Total	523	622	841	1,876
Nominations	1.40	1.32	1.69	1.51
Competitiveness				
$\frac{\text{Winners}}{\text{Nominees}}$	5.40	5.30	2.91	4.09
$\frac{\text{Winners' nominations}}{\text{Total nominations}}$	12.7	12.7	12.7	10.3

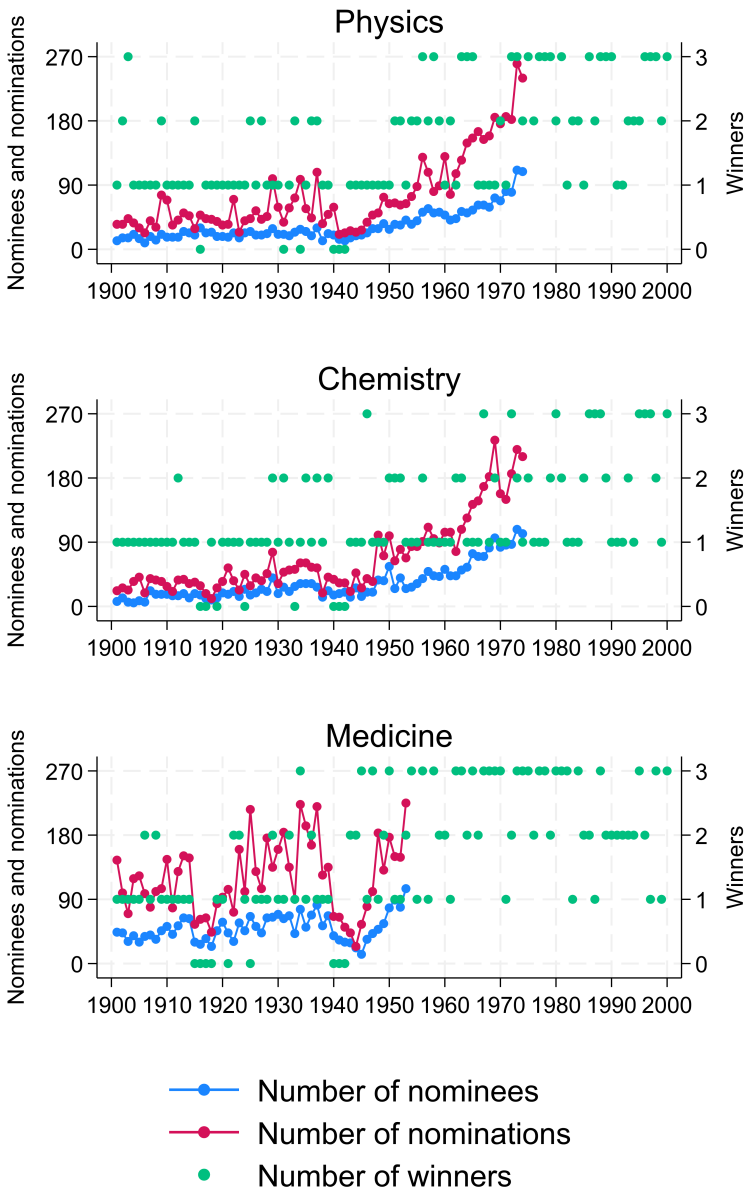
Notes: The data are sourced from the Nobel Prize API and the official Nomination Archive. It includes all Nobel laureates in Physics, Chemistry, and Medicine in the 20th century, as well as nominees in Physics and Chemistry from 1901 to 1974, and in Medicine up to 1953.

Figure 1 displays the annual number of Nobel Prize nominations, nominees, and winners in Physics, Chemistry, and Medicine throughout the 20th century. The number of winners per year, shown as green dots, ranges from one to three, with no clear or consistent pattern, reflecting the discretionary nature of the Nobel Committee's decisions. In some years, particularly during the World Wars, no prizes were awarded.[5] In contrast to the irregularity in award decisions, the number of nominations (red line) and nominees (blue line) increases steadily over time across all three

[5]Despite annual nominations, the Nobel Prize in Physics was not awarded in 1916, 1931, 1934, and 1940–42; in Chemistry, in 1916–17, 1919, 1924, 1933, and 1940–42; and in Medicine, in 1915–18, 1921, 1925, and 1940–42.

disciplines, indicating rising levels of competition and growing global interest in scientific recognition. As science expanded and matured over the century, more individuals were deemed worthy of nomination, making the Nobel Prize increasingly competitive.

Figure 1. Nobel Prize Nominations, Nominees, and Winners (1901–2000)



Notes: The data are sourced from the Nobel Prize API and the official Nomination Archive. It includes all Nobel laureates in Physics, Chemistry, and Medicine in the 20th century, as well as nominees in Physics and Chemistry from 1901 to 1974, and in Medicine up to 1953. A single nominator may nominate multiple candidates, and two nominators may jointly nominate one or more candidates.

3.2. **Patent Data.** I link 466 laureates and 1,876 non-winning nominees to their U.S. patent records between 1900 and 2000 using data from Google Patents. The matching procedure is described in detail in Appendix C.

Summary statistics of the patent data are presented in Table 2. Among the laureates, 55% (258 of 466) held patents granted by the USPTO, compared to 28% (522 of 1,876) of non-winning nominees. Among those who patented, laureates held an average of 13.7 patents, while non-winning nominees averaged slightly more, at 14.3 patents.

Table 2. Summary of Patents of Nobel Laureates and Nominees

	Physics	**Chemistry**	**Medicine**	**Total**
Nobel laureates (1901–2000)				
Number of laureates	161	133	172	466
Number of patentees	91	83	84	258
Total patents (1900–2000)	1,223	1,486	835	3,544
Patents per patentee	13.44	17.90	9.94	13.74
Non-winning nominees				
Number of nominees	523	622	841	1,876
Number of patentees	220	297	65	522
Total patents (1900–2000)	4,049	3,924	635	7,500
Patents per patentee	18.40	13.21	9.77	14.37

Notes: Summary statistics of patent records for Nobel laureates and nominees in the 20th century. Data on laureates and nominees are sourced from the Nobel Prize API and the Nomination Archive. The patent matching procedure is described in Appendix C.

Notably, several non-winning nominees were highly prolific inventors. For example, Edwin Herbert Land—co-founder of the Polaroid Corporation—held 468 patents. Table A2 lists the top ten patentees in both groups.

U.S. patenting was not limited to American inventors. Jacques Monod, a French biochemist and Nobel laureate in Medicine in 1965, was granted three U.S. patents. Patent activity also varied by discipline: laureates and nominees in Physics and Chemistry had higher average patent counts (ranging from 13.2 to 18.4 patents per patentee) compared to those in Medicine (9.9 patents per patentee).

I use historical patent data files from Marco et al. (2015) and follow the USPTO classification to define technological fields. This system divides technology into 445 narrowly defined technology classes. To account for the quality of innovation, I use patent citations as a quality-adjusted measure. I extend the NBER citation dataset by Hall et al. (2001) which covers patents granted between

1976 and 2006 to include citations for patents applied between 1900 and 1975. To study potential mechanisms, I draw on data on government-funded research from Fleming et al. (2019), as well as inventor-level data from the PATSTAT Spring 2023 Edition.

Not all scientific discoveries are patented. For example, Max Theiler won a Nobel Prize in Medicine in 1951 for his research on yellow fever and the development of a vaccine in the 1930s. [6] He held no patents with the USPTO. The effects on patenting may therefore capture only a part of the Nobel effect of scientific research. Studying publications gives a broader sense of how the Nobel Prize would affect the broader research activity.

3.3. **Publication Data.** For data on scientific publications, I use the Microsoft Academic Graph (MAG), Version 2021-09-13, a comprehensive database containing information on over 265 million papers. I conduct two main analyses. In the first analysis, I focus on a curated sample of publications from the top 100 journals for each of the seven relevant disciplines, based on the SCImago Journal Rank (SJR) for the year 2000.[7] This yields a dataset of 420 journals, 4.2 million publications spanning the years 1943 and 2000. Each record includes information on paper title, journal title, authors' names, and year of publication. This approach offers two key advantages: (1) it minimizes noise caused by entry and exit of journals over time, and (2) it ensures that the analysis centers on high-impact journals.

The second analysis draws on PubMed, a biomedical and life sciences literature database containing over 37 million references. I use Version 38 (June 14, 2025) compiled by Hughey and Schoenbachler (2025). PubMed IDs are also available in the MAG database, facilitating linkage. Since PubMed incorporates the MEDLINE—the National Library of Medicine journal citation data base, which started in the 1960s and includes articles dating back to 1946, I limit my analysis to the post-1960. This results in a sample of 12.4 million publications between 1960 and 2000.

Unlike the earlier analysis, which compares laureate and nominee fields across Physics, Chemistry, and Medicine, the PubMed-based analysis focuses solely on the Nobel Prize in Medicine. I compare Nobel-winning fields to fields not yet awarded, as nomination data for Medicine are only available up to 1953. A major advantage of the PubMed dataset is the availability of grant and funding information, allowing me to control for funding as a driver of research activity.

[6] The significance of his work was only recognized years later, once the vaccine's effectiveness was confirmed.

[7] The SCImago Journal & Country Rank (SJR) system divides journals into 27 main subject areas (disciplines) based on the Scopus Classification. The 7 relevant disciplines are: (1) Physics and Astronomy, (2) Chemistry, (3) Medicine, (4) Materials Science, (5) Biochemistry, Genetics and Molecular Biology, (6) Chemical Engineering, and (7) Immunology and Microbiology. I also add three top multidisciplinary journals—Nature, Science, and PNAS.

As with the patent data, the first step is to link scientists to their publications. Li et al. (2019) compile publication data for 545 of 590 Nobel laureates (92.4%) in the hard sciences between 1901 to 2016, including prize-winning papers.[8] For instance, their data identify seven publications by Max Theiler between 1930 and 1956 in journals such as *Science*, *The Journal of Experimental Medicine*, and *The American Journal of Tropical Medicine and Hygiene*.

The key challenge lies in matching non-winning nominees to their publications in MAG. I perform the matching using first name, last name, and middle initial. To reduce false positives, particularly with common names, I incorporate additional identifiers such as birth and death years and, when available, author affiliation. The key challenge remains in matching the non-winning nominees to their publications. I perform this matching in the MAG data using first name, last name, middle initial. To reduce false positives—particularly for common names–I incorporate additional identifying details, such as birth and death years, and where available, author affiliation. To further improve match quality, I collect biographical memoirs of scientists. Many nominees were members of the National Academy of Sciences or the Royal Society, which publish memoirs that include comprehensive bibliographies. These sources significantly enhance the precision of the matching process. Full details are provided in Appendix C.

MAG assigns publications to fields of study arranged in a hierarchical classification system. However, Färber and Ao (2022) document notable shortcomings in this classification, e.g., fields may be misassigned or the hierarchy may be inconsistently applied. As an alternative, Kim and Moser (2025) in their study on the effects of parenthood on female scientists' productivity, construct field classifications using k-means clustering.

In my study, I instead focus on the scientific concepts captured in publication titles and abstracts. Specifically, I examine bigrams (two consecutive words, e.g., *protein synthesis*) and trigrams (three consecutive words, e.g., *genetic regulatory mechanism*). I use data from Arts et al. (2025), who extracted bigrams and trigrams from the titles and abstracts of all publications in MAG. To improve precision, I apply an additional cleaning procedure to remove generic or non-scientific phrases (e.g.,*story unfold*, *alter the interaction*) that do not reflect meaningful scientific content. Figure A3 shows the frequency of bigram *protein synthesis* and the trigram *synthesis of enzyme* over time in

[8]Prize-winning papers are identified through the Nobel lectures, which often reference the prize-winning work. When not explicitly cited, a referenced paper is classified as prize-winning if it meets four conditions: (1) the laureate is an author, with matching full name (including middle name or initial); (2) the publication date aligns with the prize period; (3) institutional and coauthor details match known information; and (4) the topic corresponds to the prize motivation. If multiple papers qualify, the most cited is selected.

MAG, as well as in my two subsamples (top journals and PubMed). The series from the subsamples closely track those from MAG, suggesting that the focus on selected journals does not substantially limit generalizability.

See Table 3 for summary statistics of publication data. For 138 Nobel laureates who receive the prize between 1950 and 1974, Li et al. (2019) identify 12,119 publications, of which 169 are classified as prize-winning papers. Notably, 84% (142 out of 169) of these appear in the set of top journals used in my analysis, suggesting the journal ranking successfully capture high-impact, influential publications.

From the abstracts and titles of these papers, 837 bigrams and 821 trigrams are identified. I filter out n-grams that do not reflect meaningful scientific concepts, using criteria based on grammatical structure, ambiguity, typographical errors, informal language, and nonstandard terminology. See Table A10 for a full list of exclusion criteria and examples. After apply these filters, I retain 731 "distilled" winning bigrams and 710 "distilled" winning trigrams.

For 765 non-winning nominees, I locate 166 biographical memoirs from the National Academy of Sciences and the Royal Society, which help with the identification of 18,293 publications, 5,906 of which appear in top journals. This non-winning sample yields 7,418 bigrams and 4,074 trigrams after filtering.

3.4. **Sample Selection.** The main analysis examines the effects of Nobel Prizes awarded between 1950 and 1974 on innovation and scientific publications through 1990. The period from 1943 until 1949 serves as the pre-treatment window. Notably, no Nobel Prizes were awarded in any category between 1940 and 1942 due to the German occupation of Norway. Tables A3 and A4 provide summary statistics of patents and publications for this sample. Given the interrelated nature of the three scientific disciplines, I pool them in the main analysis. In several instances, the work awarded by prizes in a discipline has been of considerable value to the other, illustrating how the borderlands of different sciences overlap.[9]

[9]The Nobel Prize in Physiology or Medicine has often been awarded to researchers outside of traditional medical faculties whose work nonetheless proved foundational to medical science. Krogh (1920), Spemann (1935), and Medawar (1960) were zoologists; Morgan (1933) and Muller (1946) were geneticists; Hill (1922) a biophysicist; von Békésy(1961) a physicist; and Dam (1943), Chain (1945), Müller (1948), and Reichstein (1950) were organic chemists. Conversely, the Nobel Prize in Chemistry has frequently recognized scientists whose work was conducted in the medical domain, yielding results of major importance to both medicine and biochemistry. These include Pregl (1923) for organic microanalysis; Sumner (1946) for enzyme crystallization; Northrop (1946) and Stanley (1946) for purification of enzymes and virus proteins; du Vigneaud (1955) for synthesizing a polypeptide hormone; Todd (1957) for work on nucleotides and coenzymes; and Sanger (1958) for determining the structure of proteins, especially insulin (Liljestrand, 1962, pp.139-140).

Table 3. Summary of Publications of Nobel Laureates and Nominees

	Chemistry	Physics	Medicine	Total
Nobel laureates (1950–1974)				
Laureates	36	47	55	138
Papers	4,119	3,111	4,889	12,119
Winning papers	42	46	81	169
Winning papers in top journals	30	41	71	142
Winning bigrams	138	340	365	837
Winning trigrams	120	278	424	821
"Distilled" winning bigrams	121	293	323	731
"Distilled" winning trigrams	103	224	384	710
Non-winning nominees (1950–1974)				
Nominees	436	365	49	765
Memoirs	94	83	15	166
Papers	12,545	5,916	462	18,293
Papers in top journals	4,765	1,169	60	5,906
Non-winning bigrams	5,663	1,759	53	7,418
Non-winning trigrams	3,287	764	20	4,074

Notes: Summary statistics of publication records for Nobel laureates and nominees in the 20th century. Data on laureates and nominees are sourced from the Nobel Prize API and the Nomination Archive. The publication matching procedure is described in Appendix C.

As part of the robustness checks, I conduct subsample analyses by decade, focusing separately on Nobel Prizes awarded in the 1950s and 1960s. I also report discipline-specific results for Physics and Chemistry to assess whether the overall effects are driven by any single discipline.

3.5. **Defining Treatment and Treated Year.** A patent class is defined as treated if it corresponds to the technological field of a Nobel laureate in the 20 years preceding the award. This reflects the so-called recency rule, which stems from Alfred Nobel's instruction that prizes be awarded to those who have "conferred the greatest benefit to humankind during the preceding year." In practice, this guideline has been interpreted more flexibly, allowing time for the significance of a discovery to be fully recognized.

As Norrby (2002) notes, the discoveries honored by Nobel Prizes are typically made 10 to 20 years prior to the award. This is confirmed by the distribution shown in Figure A1. Across all 20th-century Nobel Prizes in the "hard" sciences, the average lag between discovery and recognition is

15.7 years. For the subset of prizes awarded between 1950 and 1974 (the focus of my main analysis) the average lag is 14.9 years.

For each treated patent class, I define the first-treated year as the year in which the laureate who patented in this class received the Nobel Prize. I consider a topic to be treated beginning in the first year the Nobel laureates won and all years thereafter. For example, Donald Arthur Glaser received the Nobel Prize in Physics in 1960 for his invention of the bubble chamber. He had 25 patents granted by the USPTO, 7 of which were filed before 1960. These seven patents span four classes: 270 (Sheet-material associating), 271 (Sheet feeding or delivering), 118 (Coating apparatus), and 294 (Handling: hand and hoist-line implements). These four classes are thus included in the treated group, with 1960 designated as the first-treated year. See Table A5 for a complete list of Glaser's patents.

Since I focus on Nobel-winning classes from 1950 to 1974, I refine the control group by excluding classes that won before (1943–1949) or after (1975–1990) this window. This ensures the comparison is strictly between treated classes and the classes of nominees who never won during the sample period (1943–1990). Figure A2 illustrates this refinement process. The final sample consists of 105 treated classes and 106 control classes. Figure 2 presents the distribution of first-treated years for the 105 treated classes. Notably, five years between 1950 and 1975 have no treated classes—either because the laureates had no patents filed in the preceding 20 years, or because their relevant patent classes fall into the pre- or post-treatment periods.

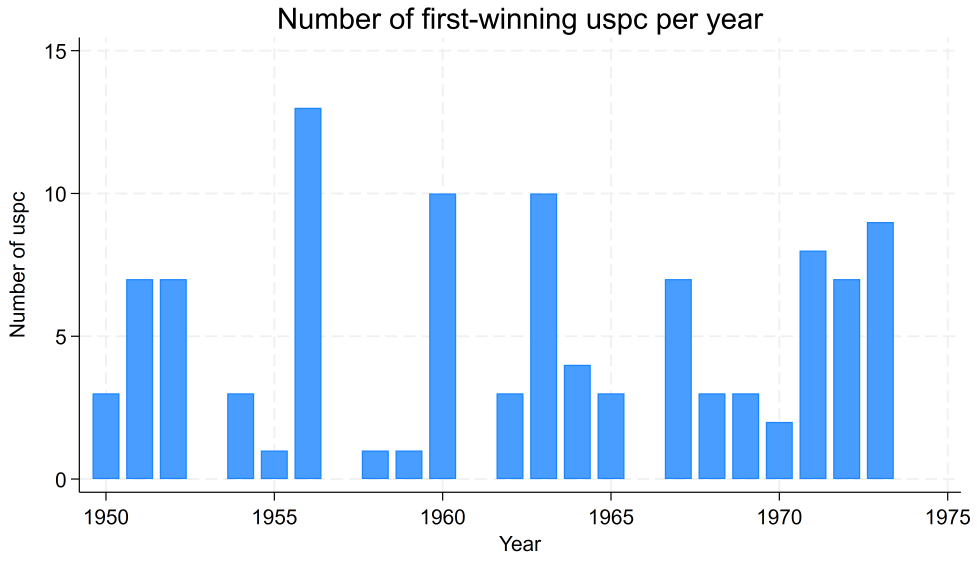
4. Empirical Strategy

4.1. **Model.** To identify the causal effect of the Nobel Prize on follow-on innovation, I use a difference-in-differences research design with staggered treatment. I estimate the model:

$$\mathbb{E}(y_{it} \mid \mathbf{X}_{it}) = f\left(\sum_{\tau \neq -1} \beta_\tau YearRealtiveWinning_{i\tau} + \alpha_i + \gamma_t + \mathbf{X}_{it}\right) \tag{1}$$

where y_{it} is the outcome of interest, e.g., the total number of patents in paten class i and year t. α_i are class fixed effects, γ_t are year fixed effects. For each class, I denote $\tau = 0$ as the first year of winning. I include a full set of event time dummies, $YearRelativeWinning_{i\tau}$. The effect at $\tau = -1$ is normalized to zero. I report only the event study coefficients estimated in the period between $\tau \geq -6$ and $\tau \leq 10$. I also control for time-varying characteristics, X_{it} that include a quadratic form of class age (the number of years that have passed since the first invention was patent in class i)

Figure 2. Distribution of Treated Years



Notes: This figure shows the distribution of the number of treated patent classes between 1950 and 1975. A patent class is considered treated if it corresponds to the technological field of a Nobel laureate who had patented in that class during the 20 years prior to receiving the award. The first-treated year is defined as the year in which the laureate received the Nobel Prize.

and the level of government funding, measured by the number of patents funded by the government for class i in time t.

Since y_{it} is count data such as the number of patents or the number of inventors, I follow the innovation literature (Azoulay et al., 2019) and estimate the model using a Poisson quasi-maximum likelihood (QML) model, in which case $f(\cdot)$ is the exponential function. In all specifications, I cluster the standard errors at the research topic level (patent class for patents, or n-gram for publications).

4.2. **Identifying Assumptions.** To interpret the results of the event study specification as causal effects of the Nobel Prize on research outcomes, I rely on two key identifying assumptions: (1) no anticipation of the treatment, and (2) parallel trends (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Borusyak et al., 2024).

4.2.1. *No anticipation.* The no anticipation assumption posits that units do not change their behavior in anticipation of treatment. I provide supporting evidence in two ways.

First, I show that observable characteristics of the technology—class age, number of annual patents, number government-funded patents, and number of inventors in the pre-period—do not predict whether a class will become a winning technology or the year of winning (See Table A6).

Second, I show that nomination dynamics are noisy and unpredictable. Having the most nominations in a given year does not guarantee a Nobel Prize. Between 1950 and 1974, 53 top-nominated nominees— those with the highest number nominations in their fields and years— did not win the prize. Table A7 lists these highly nominated but unsuccessful candidates. For example, Christopher Kelk Ingold was nominated 117 times for the prize in Chemistry but never won. Conversely, some laureates won with only a single nomination in their award year (see Table A8).[10] This unpredictability is further illustrated in Figure A1, which shows the wide variation in the lag between the completion of the prize-winning work and the award itself. The average lag is 15.7 years, with a standard deviation of 10.3, highlighting the difficulty of forecasting Nobel recognition (see Table A9).

4.2.2. *Parallel trends.* The parallel trends assumption requires that, in the absence of treatment, the difference in potential outcomes would have evolved similarly across treated and control groups, conditional on controls, unit fixed effects, and time fixed effects.

This assumption is plausible in my setting for two reasons. First, I compare technological fields associated with Nobel laureates to fields linked to prominent but ultimately uncrowned nominees—individuals who were (in some cases, repeatedly) nominated and were considered serious contenders by the Nobel committees. This comparison helps ensure that both groups are similarly influential and that their research trajectories were evolving in parallel prior to the prize.

Second, I provide empirical support for parallel trends in the pre-treatment period. In particular, I show that trends in patenting activity—measured by annual patent counts, inventor participation, and government involvement—are statistically indistinguishable across treated and control classes prior to the award (see Figures 3, 4, 6, and A4). These results indicate that, absent the Nobel Prize, innovation patterns in both groups would likely have continued on similar paths.

One potential threat to the identification assumptions is that fields or discoveries of Nobel Laureates may have already received scientific attention prior to the award. To examine this, I compare the number of major awards received by laureates and the non-winning nominees. Data on other scientific prizes for all 20th-century laureates are compiled in Kurian (2002) and digitized by Chan and Torgler (2015). I extend these data by identifying all recipients of nine major scientific awards[11]

[10] Liljestrand (1962, p.150) remarks, "A single, well-prepared proposal calling the Committee's attention to a new, prize-worthy discovery is more effective than any number of 'votes' referring briefly to some already well-known... In fact, Nobel Prizes have occasionally been awarded on a strength of a single, or only a few recommendations."

[11] These include the Copley Medal, Davy Medal, Lasker Awards, Enrico Fermi Award, Franklin Medalm Hughes Medal, Max Planck Medal, Gairdner Foundation International Award, and Faraday Medal.

and matching them to the pool of non-winning nominees. Over the 20th century, 1,173 individuals and organizations received one of these awards. Within my main sample, 65 Nobel laureates and 180 non-winning nominees were recipients. Importantly, there is no statistical difference in the number of awards received by laureates (1.35) and non-winning nominees (1.31). For both groups, the majority of the awards were conferred before the Nobel Prize (for laureates) or before the first year of nomination (for nominees). Moreover, there are no statistical differences in either the number of prior awards or the time gap for the two groups (see Table A11).

4.3. **Robustness Checks for Staggered Difference-in-Differences.** Recent contributions to the difference-in-differences literature have shown that staggered adoption of treatment can lead to biased estimates when treatment effects are heterogeneous across cohorts, even if the no-anticipation and parallel trends assumptions hold Goodman-Bacon (2021); de Chaisemartin and D'Haultfœuille (2020); Callaway and Sant'Anna (2021); Sun and Abraham (2021); Borusyak et al. (2024).

To address these concerns, I implement two key robustness checks. First, following de Chaisemartin and D'Haultfœuille (2020)), I test for the influence of negative weighting in the two-way fixed effects estimator, which can distort treatment effect estimates under heterogeneity. Second, I use the sensitivity analysis developed by Rambachan and Roth (2023) to assess how violations of the parallel trends assumption could affect my estimates.

5. Effects of the Nobel Prize on Patenting Activity

5.1. **Number of Patents.** I first examine how the Nobel recognition affects the number of patents in patent classes of the Nobel laureates. Figure 3 plots the event time coefficients and their 95% confidence interval from estimation equation 1. The magnitudes of these coefficients are presented in Column (1) of Table 4. The winning patent classes experience an increase of 49 patents per class per year compared to classes of the non-winning nominees.

5.2. **Number of Patent Citations.** To investigate whether the large increase in patenting may be driven by an increase in lower quality or "strategic" patents, I construct citation weighted patents, as a quality adjusted measure for changes in patenting (following Trajtenberg (1990)). This is calculated by weighting patents by the number of times they are cited in subsequent patents. Specifically, I define the outcome variable cwp_{ct} as:

$$cwp_{ct} = patents_{ct} + citations\, in\, patents_{1930-2006}\, to\, patents_{ct}$$

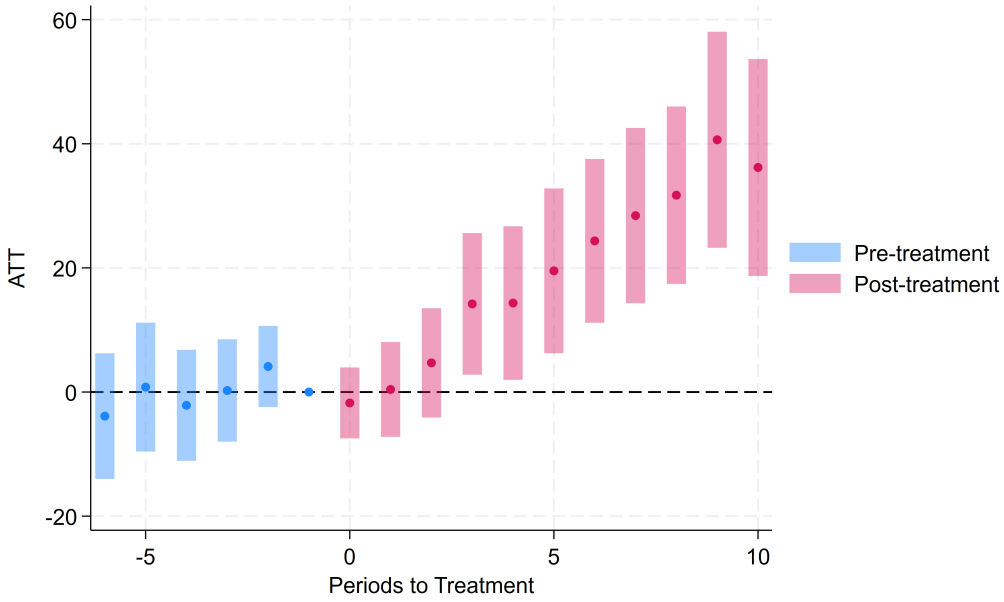


Figure 3. Effect of the Nobel Prize on Patenting

Notes: Figure 3 plots the event time coefficients and their 95% confidence intervals from estimating equation (1) for the number of patents, using class fixed effects and year fixed effects. Standard errors are clustered at the patent class level.

I extend the NBER Patent Citation Data 1976–2000 to include patents issued from 1940. Number of citations increase by 474.65 (Figure 4 and Column 2 of Table 4).

5.3. **Spillover.** Do similar non-winning patent classes experience spillover effects from Nobel-winning classes? In other words, are patent classes that are more closely related to winning classes affected differently than those that are more distant? To examine this, I measure the *distance* between each non-winning class i and the set of winning classes as the inverse of the share of inventors in class i who also hold patents in any of the winning classes. I then rank the 106 control classes by this distance metric (see Table A12).

For example, patent class 518 includes 1,770 inventors, of whom 1,149 (64.92%) also patent in the winning classes, making it the closest non-winning class. By contrast, class 482 has 13,921 inventors, but only 1,316 (9.45%) of them also patent in winning classes, making it the most distant.

Next, I compare the evolution of outcomes in winning classes to two control groups: (1) patent classes close to the winning classes, and (2) those that are more distant. As shown in Figure 5, estimated treatment effects are smaller when comparing against proximate technologies, suggesting positive spillovers from Nobel-winning classes to nearby fields.

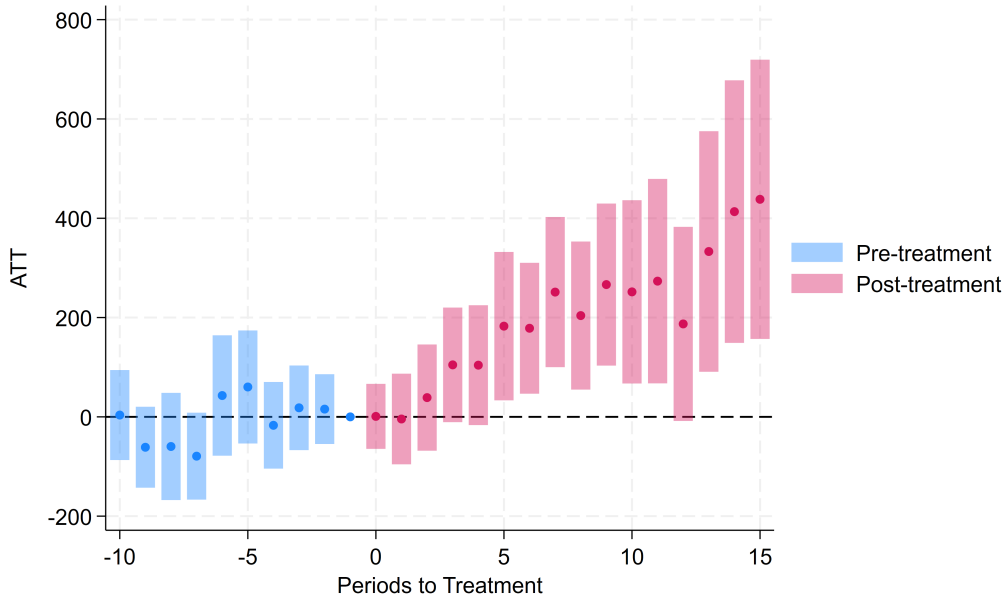


Figure 4. Effect of the Nobel Prize on Patent Citation

Notes: Figure 4 plots the event time coefficients and their 95% confidence intervals from estimating equation (1) for citations-weighted-patents, using class fixed effects and year fixed effects. Standard errors are clustered at the patent class level.

As a second test, I define adjacent technologies as a separate treatment arm by matching each winning class to its closest non-nominated class. Results indicate that these adjacent classes also benefit from exposure to Nobel-winning technologies, though effects become apparent only after year 5 following the award (see Figure A5).

5.4. **Government Funding.** I next examine whether the Nobel Prize leads to an increase in government-supported patenting activity within the technological fields of laureates. Using data from Fleming et al. (2019) that identify government-funded patents, I estimate treatment effects separately for two outcomes: (1) the number of government-funded patents funded, and (2) number of privately-funded patents. The results, presented in Columns 3 and 4 of Table 4 and illustrated in Figure 6 indicate that the observed increase in patenting is driven primarily by privately funded patents, with little to no corresponding rise in government-funded patents.

5.5. **Inventor Dynamics.** To better understand the mechanisms underlying the observed increase in patenting within Nobel-winning technologies, I examine the inventor-level dynamics using PATSTAT data covering 2.8 million inventors who patented with the USPTO between 1930 and 1990. The rise in post-award patenting could reflect three possible channels: (1) incumbents in winning

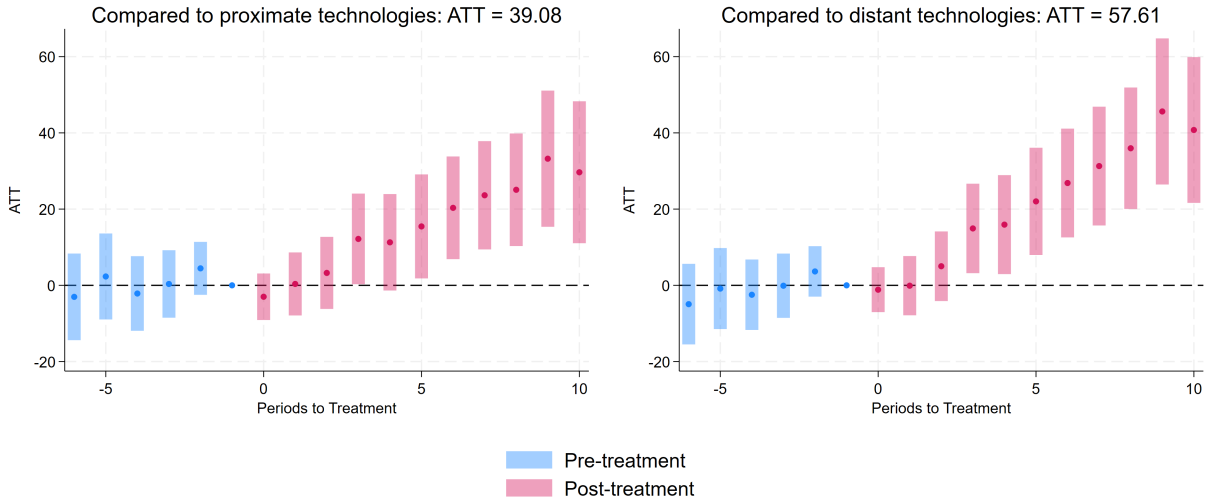
Table 4. The Nobel Prize Effects on Patenting Activity

			Patents	
	Patents	Citations	Government-funded	Privately-funded
	(1)	(2)	(3)	(4)
Year −6	−3.88	42.99	−1.37	−2.08
	(5.17)	(61.87)	(0.77)	(4.93)
Year −5	0.79	60.17	−0.99	1.81
	(5.30)	(58.07)	(0.85)	(5.00)
Year −4	−2.14	−17.01	−0.96	−1.49
	(4.56)	(44.52)	(0.73)	(4.34)
Year −3	0.24	18.20	−1.66	1.35
	(4.21)	(43.48)	(0.64)	(4.01)
Year −2	4.12	15.61	−0.29	4.38
	(3.34)	(35.84)	(0.50)	(3.20)
Year 0	−1.76	0.99	−0.15	−1.92
	(2.91)	(33.39)	(0.55)	(2.81)
Year 1	0.42	−4.32	−0.93	0.61
	(3.90)	(46.57)	(0.73)	(3.78)
Year 2	4.70	38.81	0.87	3.26
	(4.49)	(54.59)	(0.84)	(4.19)
Year 3	14.20	104.70	0.93	12.27
	(5.82)	(58.88)	(1.00)	(5.46)
Year 4	14.34	104.11	0.22	12.49
	(6.31)	(61.59)	(1.00)	(5.89)
Year 5	19.53	182.72	−0.29	17.72
	(6.78)	(76.25)	(1.03)	(6.34)
Year 6	24.35	178.46	0.91	21.19
	(6.73)	(67.25)	(1.45)	(5.97)
Year 7	28.43	251.32	1.67	24.61
	(7.21)	(77.17)	(1.47)	(6.43)
Year 8	31.72	204.03	2.26	26.74
	(7.29)	(76.08)	(1.53)	(6.40)
Year 9	40.45	266.43	2.06	35.50
	(8.88)	(83.26)	(1.67)	(8.07)
Year 10	36.19	251.76	0.18	32.84
	(8.92)	(94.16)	(1.61)	(8.15)
Observations	10,128	9,787	10,128	10,128
Estimator	Poisson	Poisson	Poisson	Poisson

Notes: Table 4 reports the estimated coefficients from equation (1) on (1) the number of patents, (2) citations-weighted-patents, (3) number of patents funded by the government, and (4) number of privately-funded patents. Effect at event time $\tau = -1$ is normalized to 0. Baseline mean denotes the mean of the outcome variable at $\tau = -1$. All specifications include year fixed effects and patent class fixed effects.

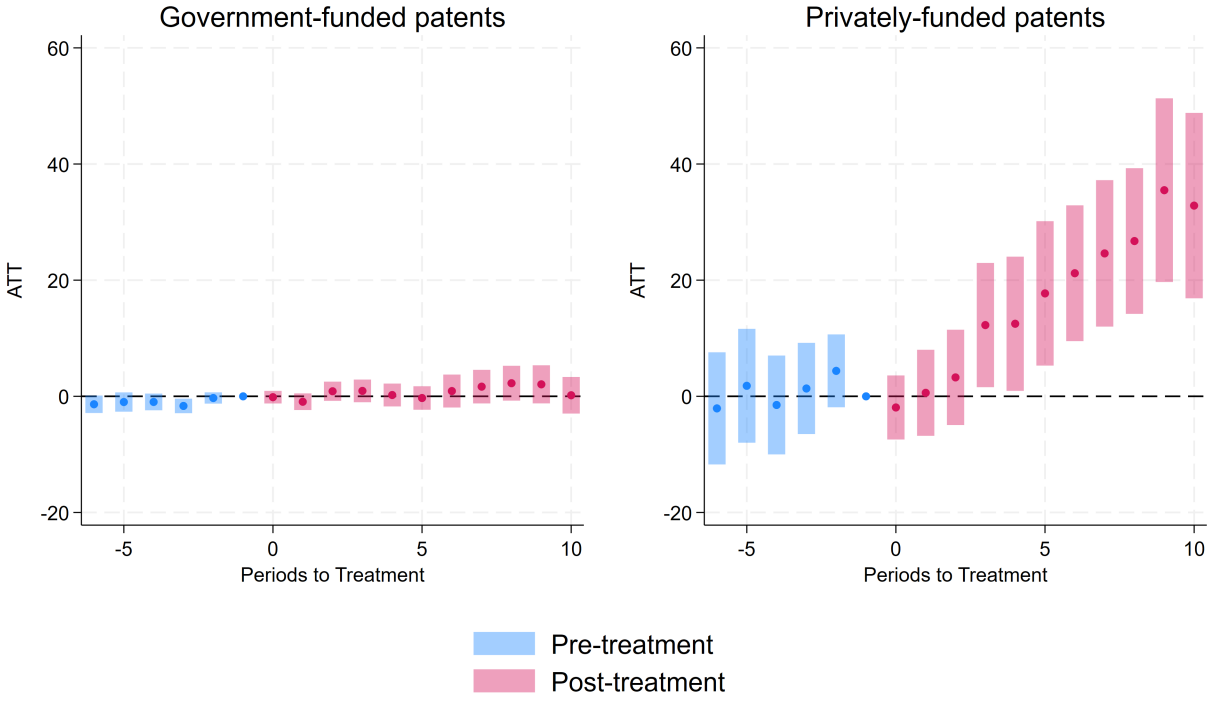
fields continuing their work, (2) inventors switching into winning fields from other technological areas, or (3) new entrants being drawn to the laureates' field after the prize.

Figure 5. Spillover



Notes: This figure compares patenting activity in Nobel-winning classes to that in non-winning nominee classes. The left panel uses technology classes proximate to the winning classes as the control group, while the right panel uses distant classes as the control group.

Figure 6. Government Funding

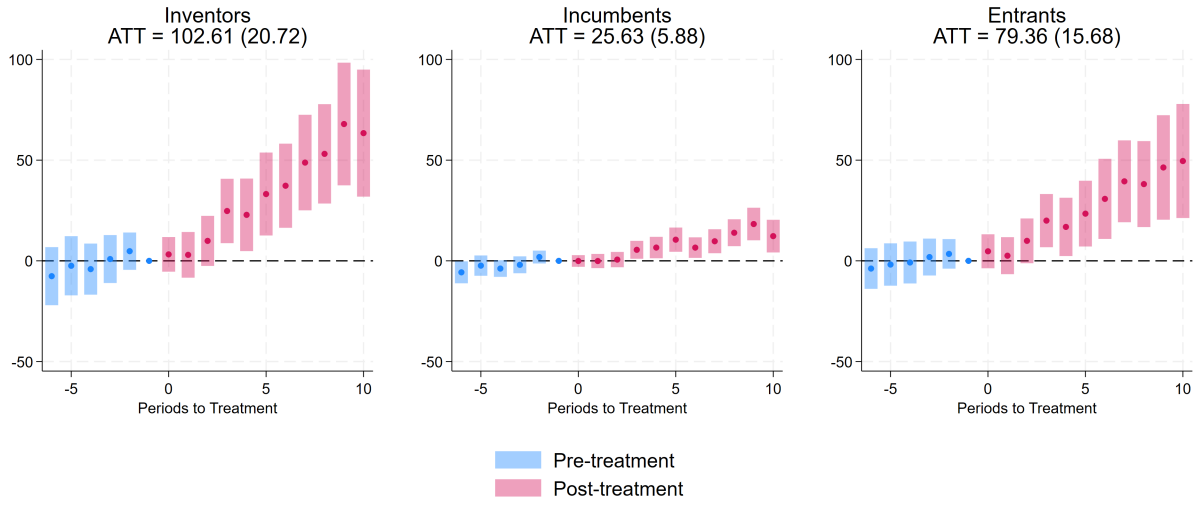


Notes: This figure compares patenting activity in Nobel-winning classes to that in non-winning nominee classes, separately for government-funded patents (left panel) and privately funded patents (right panel).

For each inventor active in class i and year t, I classify them as an *incumbent* if they held least one patent in class i prior to t, and as an *entrant* otherwise. Figure 7 and Columns (1) and (2) of Table 5 show significant increases in both incumbents and entrants in Nobel-winning classes following the award. The effect is substantially larger for entrants, with in average increase of 79.36 inventors per class per year, compared to 25.63 for incumbents.

To further unpack these dynamics, Figure A10 separates entrants into two groups: new inventors entering the patent system for the first time, and established inventors switching from other technologies into Nobel-winning classes. The results suggest that the post-award growth in patenting activity is fueled by both switching and attraction effects.

Figure 7. Inventor Dynamics



Notes: This figure plots the event time coefficients and their 95% confidence intervals from estimating equation (1) for the number of inventors, incumbents, and entrants. All specifications include patent class and year fixed effects. Standard errors are clustered at the patent class level.

Finally, I examine whether the post-award increase in innovation is driven primarily by company-owned or individual-owned patents, using sector classifications in PATSTAT. Columns (4) and (5) of Table 5 show increases for both types, but the effect is larger for company-owned patents. Notably, the increase in company-owned patents occurs with approximately a one-year lag relative to individual-owned patents.

Table 5. The Nobel Prize Effects on Inventor Dynamics

		Types of Inventors		Patent Ownership	
	Inventors	Incumbents	Entrants	Company	Individual
	(1)	(2)	(3)	(4)	(5)
Year −6	−7.60	−5.69	−.81	−1.57	0.72
	(7.35)	(2.78)	(5.14)	(1.59)	(0.54)
Year −5	−2.44	−2.37	−1.82	−1.37	1.26
	(7.50)	(2.57)	(5.37)	(1.74)	(0.86)
Year −4	−4.11	−3.83	−0.82	−1.82	0.57
	(6.47)	(2.11)	(5.31)	(1.39)	(0.78)
Year −3	0.89	−1.97	1.88	0.67	0.24
	(6.07)	(2.14)	(4.67)	(1.38)	(0.82)
Year −2	4.81	1.89	3.47	1.13	−0.46
	(4.73)	(1.62)	(3.74)	(1.19)	(0.61)
Year 0	3.22	−0.06	4.74	0.63	1.63
	(4.39)	(1.48)	(4.31)	(1.01)	(0.97)
Year 1	2.97	−0.89	2.57	0.95	3.46
	(5.79)	(0.5)	(4.69)	(1.24)	(1.55)
Year 2	9.91	0.63	9.94	2.65	3.23
	(6.34)	(1.94)	(5.67)	(1.57)	(2.17)
Year 3	24.76	5.49	19.97	4.67	7.31
	(8.15)	(2.27)	(6.73)	(1.70)	(1.94)
Year 4	22.84	6.61	16.85	5.06	2.65
	(9.19)	(2.71)	(7.38)	(2.00)	(2.26)
Year 5	33.18	10.52	23.45	7.17	5.36
	(10.50)	(3.07)	(8.33)	(2.29)	(2.74)
Year 6	37.30	6.58	30.77	7.95	6.44
	(10.65)	(2.60)	(10.15)	(2.35)	(3.08)
Year 7	48.79	9.74	39.49	9.57	8.58
	(12.10)	(3.04)	(10.37)	(2.58)	(3.75)
Year 8	53.13	13.96	38.11	11.62	8.29
	(12.58)	(3.41)	(10.89)	(2.57)	(3.31)
Year 9	67.93	18.29	46.37	12.19	9.57
	(15.53)	(4.12)	(13.23)	(3.01)	(3.63)
Year 10	63.41	12.27	49.57	13.03	10.63
	(16.09)	(4.14)	(14.45)	(3.14)	(4.09)
Observations	10,128	10,128	10,128	10,128	10,128
Estimator	Poisson	Poisson	Poisson	Poisson	Poisson

Notes: Table 5 reports the estimated coefficients from equation (1) on (1) the number of inventors, (2) the number of incumbents, (3) the number of entrants, (4) the number of corporate inventors, and (5) number of individual inventors. Effect at event time $\tau = -1$ is normalized to 0. Baseline mean denotes the mean of the outcome variable at $\tau = -1$. All specifications include year fixed effects and patent class fixed effects.

5.6. **Robustness.** I show that the effects are robust to the types of estimators that have recently been developed for the staggered difference-in-differences design, including Wooldridge (2023), Callaway and Sant'Anna (2021), Borusyak et al. (2024), and de Chaisemartin and D'Haultfœuille (2024). See Figure A6 for the results.

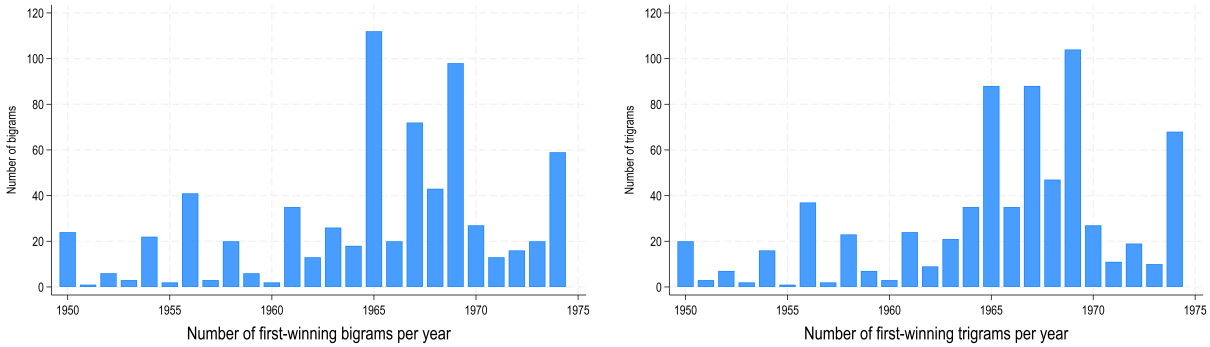
6. Effects of the Nobel Prize on Scientific Publications

In this section, I examine the effects of the Nobel Prize on scientific publications in Nobel-winning topics, measured using n-grams extracted from the titles and abstracts of prize-winning papers. I begin by analyzing publications in high-impact journals, ranked according to the SCImago Journal Rank. I then focus on the Nobel Prize in Physiology or Medicine and study its effects on publications indexed in PubMed.

6.1. **Publications in High-Impact Journals.** Figure 8 shows the distribution of first-treated years for winning bigrams and trigrams, indicating that at least one-winning n-gram is observed in every year of the main sample. Figure 9 presents the event-study estimates. The pre-treatment coefficients confirm the absence of for differential pre-trends, consistent with the identifying assumptions. For bigrams, the treatment effects begin to emerge around year 4 after the award and persist for at least a decade, suggesting a sustained increase in scientific attention to Nobel-winning topics. For trigrams, the results are noisier, but positive and statistically significant effects are evident in years 2, 3, and 5 post-award. This greater variability is not surprising: trigrams capture research topics with greater precision than bigrams, and therefore reflect more granular, and inherently more volatile, patterns of scientific attention. Taken together, the results indicate that Nobel recognition stimulates publication activity in winning topics, especially within elite journals, reinforcing the Prize's role in shaping high-impact research trajectories.

6.2. **Publications in PubMed.** As a complementary analysis, I focus on the Nobel Prize in Physiology and Medicine using publications indexed in PubMed. Two differences distinguish this exercise from preceding analyses. First, the sample covers a later period (1966–1990), since MEDLINE, the core component of PubMed, provides comprehensive coverage of medical literature only from 1966 onward. Second, because data on Nobel nominations in Medicine are only available through 1953, I compare publications in research topics of early laureates to those of later laureates, rather than contrasting winners with non-winning nominees. This approach has the advantage of concentrating on a single prize and a field-specific publication database, thereby providing both a complementary

Figure 8. Distribution of Treated Years for Winning N-Grams



Notes: This figure shows the distribution of the number of treated bigrams and trigrams between 1950 and 1975. An n-gram is treated if it appears in titles or abstracts of Nobel-winning papers. The first-treated year is defined as the year in which the laureate received the Nobel Prize.

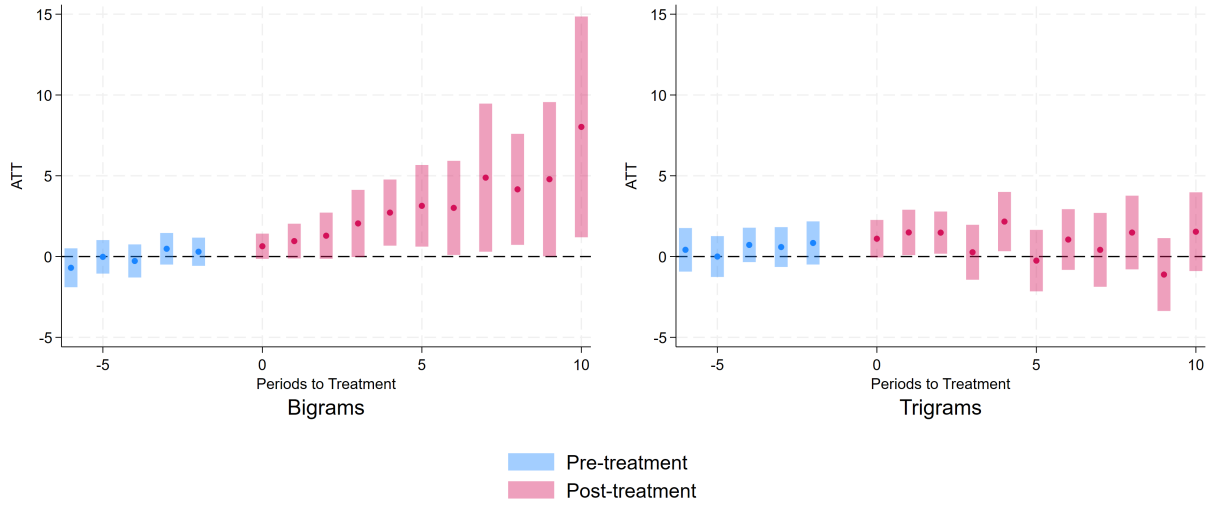


Figure 9. Effect of the Nobel Prize on Publications in Top Journals

Notes: Figure 9 plots the event time coefficients and their 95% confidence intervals from estimating equation (1) for the number of publications that contain winning bigrams (left) and winning trigrams (right), using n-gram fixed effects and year fixed effects. Standard errors are clustered at the n-gram level.

perspective and a robustness check on the main findings. Figure 10 shows that n-grams associated with Nobel laureates exhibit a clear post-award increase in publication activity, as measured by their appearance in titles and abstracts, relative to n-grams of later laureates.

Overall, the evidence from both exercises indicates that the Nobel Prize spurs measurable increases in publication activity in winning topics. Importantly, the results are consistent across

two distinct datasets, one focused on top journals across all fields and the other on a field-specific biomedical database, underscoring the robustness of the conclusion that Nobel recognition reshapes patterns of scientific output.

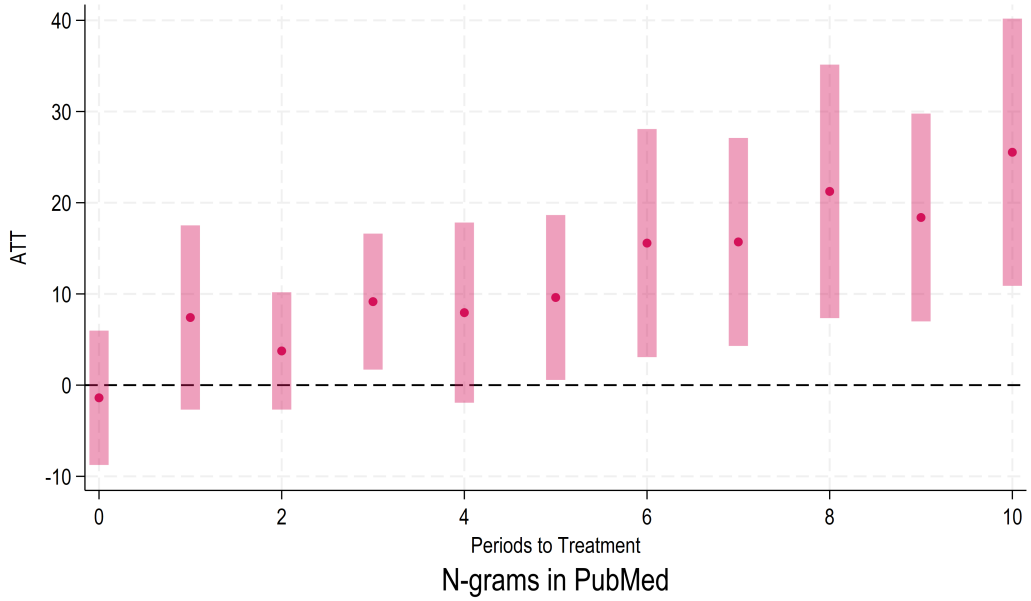


Figure 10. Effect of the Nobel Prize on Medical Publications

Notes: Figure 10 compares the number of publications with n-grams that won earlier to those with n-grams that won later. Standard errors are clustered at the n-gram level.

7. Conclusion

This paper applies a dynamic difference-in-differences design to compare Nobel laureates' fields to those of similarly eminent but non-winning nominees. The evidence shows that Nobel recognition triggers a large and sustained post-award surge in innovation within the laureates' technological classes and associated scientific topics, with adjacent areas also exhibiting delayed but substantial gains in inventive and publication activity. The mechanism is driven primarily by intensified entry: most of the growth comes from new researchers and inventors moving into the winning fields, rather than from government-backed projects. Privately funded patenting accounts for the bulk of the increase. Taken together, these findings suggest that the Nobel Prize operates as a salient coordination signal that reallocates scientific attention toward recognized ideas and stimulates exploration in neighboring domains over time.

These results carry clear implications for how scientific achievements are funded and rewarded. While competition fuels excellence, selective, high-status recognition can distort the allocation of

effort by concentrating attention on a narrow set of topics—potentially at the expense of equally promising, non-awarded areas. The policy response is not to dampen competition, but to broaden recognition by expanding the set of prestigious prizes so that multiple frontier lines can attract talent simultaneously. Recent developments point in this direction: newer awards such as the Breakthrough Prize, with its multi-field scope and growing early-career portfolio, and the Kavli Prize, which biennially honors advances in astrophysics, nanoscience, and neuroscience, exemplify a more inclusive recognition infrastructure that diversifies the focal points of scientific attention.

By documenting how prestige-based recognition reshapes inventive entry and topic diffusion, this paper highlights prizes as policy-relevant levers in the innovation system. A diversified ecosystem of high-status awards can preserve the motivational benefits of tournament-like competition while mitigating the risks of excessive concentration, sustaining exploration across a broader scientific frontier. Such an ecosystem should complement—rather than substitute—core funding institutions: public research support remains foundational to the knowledge base on which private effort builds. But crucially, Nobel-induced surges in activity are not primarily a funding artifact; they reflect an attention-and-entry phenomenon, one that recognition policy can help channel more evenly across fields.

References

Arts, Sam, Nicola Melluso, and Reinhilde Veugelers, "Beyond Citations: Measuring Novel Scientific Ideas and their Impact in Publication Text," *The Review of Economics and Statistics*, 01 2025, pp. 1–33.

Azoulay, Pierre, Christian Fons-Rosen, and Joshua S. Graff Zivin, "Does Science Advance One Funeral at a Time?," *American Economic Review*, August 2019, *109* (8), 2889–2920.

_____, **Joshua S. Graff Zivin, and Jialan Wang**, "Superstar Extinction," *The Quarterly Journal of Economics*, 2010, *125* (2), 549–589.

Babutsidze, Zakaria and Mark McCabe, "Scientific Prizes and Post-Award Attention: Evidence from the Nobel Prize in Economics," 2024. Working Paper.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "Who Becomes an Inventor in America? The Importance of Exposure to Innovation," *The Quarterly Journal of Economics*, 2018, *134* (2), 647–713.

Borjas, George J. and Kirk B. Doran, "The Collapse of the Soviet Union and the Productivity of American Mathematicians," *The Quarterly Journal of Economics*, 2012, *127* (3), 1143–1203.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event-Study Designs: Robust and Efficient Estimation," *The Review of Economic Studies*, 02 2024, *91* (6), 3253–3285.

Brunt, Liam, Josh Lerner, and Tom Nicholas, "Inducement Prizes and Innovation," *The Journal of Industrial Economics*, 2012, *60* (4), 657–696.

Burstein, Michael J. and Fiona E. Murray, "Innovation Prizes in Practice and Theory," *Harvard Journal of Law & Technology*, 2016, *29* (2), 401–453.

Callaway, Brantly and Pedro H.C. Sant'Anna, "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 2021, *225* (2), 200–230. Themed Issue: Treatment Effect 1.

Chan, Ho Fai and Benno Torgler, "The Implications of Educational and Methodological Background for the Career Success of Nobel Laureates: An Investigation of Major Awards," *Scientometrics*, 2015, *102*, 847–863.

Congressional Research Service, "The Nobel-prize Awards in Science as a Measure of National Strength in Science: Report," Technical Report v. 4, Library of Congress 1986.

de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, September 2020, *110* (9), 2964–96.

_____ **and** _____, "Difference-in-Differences Estimators of Intertemporal Treatment Effects," *The Review of Economics and Statistics*, 02 2024, pp. 1–45.

Feldman, Burton, *The Nobel Prize: A History of Genius, Controversy, and Prestige*, New York: Arcade Publishing, 2000.

Fleming, L., H. Greene, G. Li, M. Marx, and D. Yao, "Government-funded Research Increasingly Fuels Innovation," *Science*, 2019, *364* (6446), 1139–1141.

Färber, Michael and Lin Ao, "The Microsoft Academic Knowledge Graph Enhanced: Author Name Disambiguation, Publication Classification, and Embeddings," *Quantitative Science Studies*, 04 2022, *3* (1), 51–98.

Goodman-Bacon, Andrew, "Difference-in-differences with Variation in Treatment Timing," *Journal of Econometrics*, 2021, *225* (2), 254–277. Themed Issue: Treatment Effect 1.

Gross, Daniel P. and Bhaven N. Sampat, "America, Jump-Started: World War II R&D and the Takeoff of the US Innovation System," *American Economic Review*, December 2023, *113* (12), 3323–56.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools," 2001. NBER Working Paper 8498.

Ham, John C. and Bruce A. Weinberg, "Novelty, Knowledge Spillovers and Innovation: Evidence from Nobel Laureates," 2019. Working Paper.

Hargittai, István, *The Road to Stockholm: Nobel Prizes, Science, and Scientists*, Oxford University Press, 03 2002.

Hughey, Jacob and Joshua Schoenbachler, "PMDB: A Relational Database for PubMed, Version v38," June 2025.

Hunt, Jennifer and Marjolaine Gauthier-Loiselle, "How Much Does Immigration Boost Innovation?," *American Economic Journal: Macroeconomics*, April 2010, *2* (2), 31–56.

Jin, Ching, Yifang Ma, and Brian Uzzi, "Scientific Prizes and the Extraordinary Growth of Scientific Topics," *Nature Communications*, 2021, *12* (1), 5619.

Jones, Benjamin F., "Age and Great Invention," *The Review of Economics and Statistics*, 2010, *92* (1), 1–14.

_____ **and Bruce A. Weinberg**, "Age Dynamics in Scientific Creativity," *Proceedings of the National Academy of Sciences*, 2011, *108* (47), 18910–18914.

Kim, Scott and Petra Moser, "Women in Science. Lessons from the Baby Boom," *Econometrica*,

2025. forthcoming.

Kurian, George Thomas, *The Nobel Scientists: A Biographical Encyclopedia*, Amherst, New York: Prometheus Books, 2002.

Li, Dawei, Yijuan Wang, and Zhi-Ping Liu, "Academic Background of Nobel Prize Laureates Reveals the Importance of Multidisciplinary Education in Medicine," *Social Sciences & Humanities Open*, 2021, *3* (1), 100114.

Li, Jichao, Yian Yin, Santo Fortunato, and Dashun Wang, "A Dataset of Publication Records for Nobel laureates," *Scientific Data*, 2019, *6* (33), 1–10.

———, ———, ———, **and** ———, "Scientific Elite Revisited: Patterns of Productivity, Collaboration, Authorship and Impact," *Journal of the Royal Society Interface*, 2020, *17: 20200135.*

Liljestrand, Göran, "The Prize in Physiology or Medicine," in The Nobel Foundation, ed., *Nobel: The Man and his Prizes*, 2 ed., Amsterdam: Elsevier, 1962, pp. 131–344.

Ma, Yifang and Brian Uzzi, "Scientific Prize Network Predicts Who Pushes the Boundaries of Science," *Proceedings of the National Academy of Sciences*, 2018, *115* (50), 12608–12615.

Marco, Alan C., Michael Carley, Steven Jackson, and Amanda F. Myers, "The USPTO Historical Patent Data Files: Two Centuries of Innovation," June 2015. Available at SSRN: https://ssrn.com/abstract=2616724 or http://dx.doi.org/10.2139/ssrn.2616724.

Mitsis, Pandelis, "The Nobel Prize Time Gap," *Humanities and Social Sciences Communications*, 2022, *9* (1), 407.

Moser, Petra, Alessandra Voena, and Fabian Waldinger, "German Jewish Émigrés and US Invention," *American Economic Review*, October 2014, *104* (10), 3222–55.

——— **and** ———, "Compulsory Licensing: Evidence from the Trading with the Enemy Act," *American Economic Review*, February 2012, *102* (1), 396–427.

——— **and Bang Dinh Nguyen**, "Operation Paperclip: Nazi Scientists and U.S. Innovation," 2025. Working Paper.

——— **and Tom Nicholas**, "Prizes, Publicity and Patents: Non-Monetary Awards as a Mechanism to Encourage Innovation," *The Journal of Industrial Economics*, 2013, *61* (3), 763–788.

Myers, Kyle, "The Elasticity of Science," *American Economic Journal: Applied Economics*, 2020, *12* (4), 103–34.

Nicholas, Tom, "Hybrid Innovation in Meiji, Japan," *International Economic Review*, 2013, *54*

(2), 575–600.

Norrby, Erling, "A Century of Nobel Prizes," *Proceedings of the American Philosophical Society*, 2002, *146* (4), 323–336.

Novosad, Paul, Sam Asher, Catriona Farquharson, and Eni Iljazi, "Access to Opportunity in Sciences: Evidence from the Nobel Laureates," 2024. Working Paper.

Rambachan, Ashesh and Jonathan Roth, "A More Credible Approach to Parallel Trends," *The Review of Economic Studies*, 02 2023, *90* (5), 2555–2591.

Reschke, Brian P., Pierre Azoulay, and Toby E. Stuart, "Status Spillovers: The Effect of Status-conferring Prizes on the Allocation of Attention," *Administrative Science Quarterly*, 2018, *63* (4), 819–847.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199. Themed Issue: Treatment Effect 1.

The Nobel Foundation, *The Nobel Prize: The First 100 Years*, London: Imperial College Press and Word Scientific Publishing, 2001.

Trajtenberg, Manuel, "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *The RAND Journal of Economics*, 1990, *21* (1), 172–187.

Truffa, Francesca and Ashley Wong, "Undergraduate Gender Diversity and the Direction of Scientific Research," *American Economic Review*, July 2025, *115* (7), 2414–48.

Weinberg, Bruce A. and David W. Galenson, "Creative Careers: The Life Cycles of Nobel Laureates in Economics," *De Economist*, 2019, *167* (3), 221–239.

Wooldridge, Jeffrey M, "Simple approaches to nonlinear difference-in-differences with panel data," *The Econometrics Journal*, 08 2023, *26* (3), C31–C66.

Zuckerman, Harriet, "Nobel Laureates in Science: Patterns of Productivity, Collaboration, and Authorship," *American Sociological Review*, 1967, *32* (3), 391–403.

Appendix A. Additional Tables and Figures

Table A1. Nomination data related to Edwin Herbert Land

Year	Field	Nominator for Land	Total Nominations	Total Nominators	Total Nominees	Winners (Nominations Received)
1954	Physics	Harlow Shapley (Harvard)	74	53	35	Max Born (5) Walther Bothe (7)
1972	Chemistry	George Porter (London)	186	147	87	Christian B. Anfinsen (2) Stanford Moore (2) William H. Stein (1)
1973	Physics	Karl Helmer Gustavson (Stockholm)	260	133	111	Leo Esaki (*) Ivar Giaever (*) Brian David Josephson (*)
1973	Chemistry	George Porter (London)	220	160	108	Ernst Otto Fischer (3) Geoffrey Wilkinson (1)
1974	Physics	Robert Burns B Woodward (Cambridge)	240	135	109	Sir Martin Ryle (7) Antony Hewish (3)
1974	Chemistry	George Porter (London)	210	151	102	Paul J. Flory (13)

Notes: Nomination data are from the Nomination Archive, as of June 1, 2025. George Porter won the Nobel Prize in Chemistry in 1967. An asterisk (*) indicates that data have been withheld in accordance with §8 of the statutes governing the Nobel Archive of the Royal Swedish Academy of Sciences—typically because the nominee is still living.

Table A2. Top Patentees Among Nobel Laureates and Nominees

Rank	Name	Year	Field	Number of Patents
Nobel Laureates				
1	Giulio Natta	1963	Chemistry	117
2	Herbert C. Brown	1979	Chemistry	104
3	William Bradford Shockley	1956	Physics	83
4	Leopold Ruzicka	1939	Chemistry	82
5	Charles Thomson Rees Wilson	1927	Physics	76
6	Carl Bosch	1931	Chemistry	75
7	K. Alexander Müller	1987	Physics	70
8	Ernst Otto Fischer	1973	Chemistry	69
9	George H. Hitchings	1988	Medicine	69
10	Robert Woodrow Wilson	1978	Physics	67
Non-winning Nominees				
1	Edwin Herbert Land	–	–	468
2	Thomas Edison	–	–	337
3	Vladimir N. Ipatieff	–	–	214
4	Karl A. Folkers	–	–	126
5	Karl Miescher	–	–	123
6	Vladimir K. Zworykin	–	–	116
7	Erwin Wilhelm Müller	–	–	111
8	Lee de Forest	–	–	101
9	Carl Djerassi	–	–	100
10	Walter Reppe	–	–	99

Notes: This table lists the top 10 patentees among Nobel laureates and non-winning nominees. For Nobel laureates, the year of the award and field are shown, along with their total number of patents.

Table A3. Summary of Patents — Main Sample

	Physics	Chemistry	Medicine	Total
Nobel laureates (1943–1990)				
Number of laureates	93	74	109	276
Number of patentees	61	52	58	171
Total patents (1900–2000)	779	876	676	2,331
Patents per patentee	12.77	16.85	11.66	13.63
Non-winning nominees (1943–1974)				
Number of nominees	397	468	247	1,044
Number of patentees	171	226	33	394
Total patents (1900–2000)	2746	3319	474	5,571
Patents per patentee	16.06	14.69	14.36	14.14

Notes: Summary statistics of patent records for Nobel laureates and nominees in the main sample. Data on laureates and nominees are sourced from the Nobel Prize API and the Nomination Archive. The patent matching procedure is described in Appendix C.

Table A4. Summary of Publications — Main Sample

	Chemistry	Physics	Medicine	Total
Nobel laureates (1943–1990)				
Laureates	36	47	55	138
Papers	4,119	3,111	4,889	12,119
Winning papers	42	46	81	169
Winning papers in top journals	30	41	71	142
Winning bigrams	138	340	365	837
Winning trigrams	120	278	424	821
"Distilled" winning bigrams	121	293	323	731
"Distilled" winning trigrams	103	224	384	710
Non-winning nominees (1943–1974)				
Nominees	436	365	49	765
Memoirs	94	83	15	166
Papers	12,545	5,916	462	18,293
Papers in top journals	4,765	1,169	60	5,906
Non-winning bigrams	5,663	1,759	53	7,418
Non-winning trigrams	3,287	764	20	4,074

Notes: Summary statistics of publication records for Nobel laureates and nominees in the main sample. Data on laureates and nominees are sourced from the Nobel Prize API and the Nomination Archive. The publication matching procedure is described in Appendix C.

Table A5. Patents of Donald A. Glaser

id	Title	Co-inventor(s)	Filed	Granted	USPC
2568224	Paper gathering machine	Carl W. Didde	1948	1951	270
2846214	Sheet detector for paper gathering apparatus	Carl W. Didde	1955	1958	270
2937868	Sheet supporting and handling apparatus	Carl W. Didde	1958	1960	271
3034476	Apparatus for applying adhesive to sheet material	Carl W. Didde	1958	1962	118
3019013	Paper gathering and treating apparatus	Carl W. Didde	1958	1962	270
3122391	Self-valving sucker assembly	Carl W. Didde, Jr., Harry E. Higgins	1960	1964	294
3072398	Pile lift assembly	Lawrence H. Cozad, Carl W. Didde	1960	1963	271
3061303	Self-centering parallel guide assembly	Leonard C. Warren	1961	1962	271
3103125	Register compensating means for rotary members in web processing apparatus	Orville V. Dutro, Sherman H. Hewson	1961	1963	474
3111250	Modular apparatus for processing web material	Orville V. Dutro, Sherman H. Hewson	1961	1963	226
3093371	Bottom feed apparatus for sheet handling equipment	Leonard C. Warren	1961	1963	271
3385123	Drive mechanism for roll duplicator	Woodrow W. Pendleton, Carlton A. Bird	1965	1968	474
3393755	Apparatus for engraving, carving, cutting or chipping metals, wood, stone or the like	John R. Rohner	1966	1968	173
3544225	Peak reading optical density measuring system	Willard H. Wattenburg, Hector O. Conde	1967	1970	356
3476291	Method and apparatus for dispensing measured quantities of liquids	—	1968	1969	222
3658319	Vacuum operated sheet feeding mechanism for newspaper inserter	—	1969	1972	271
3656738	Conveyor operated misfeed control mechanism for multiple station article delivery apparatus	Lyle V. Dutro, Woodrow W. Pendleton	1970	1972	270
3880077	Tinting unit for offset printing press	Agustin Mena	1973	1975	101
3871280	Glue applying assembly for multiple web-fed paper handling apparatus	—	1973	1975	118
4694912	Controlled impact power tool	—	1986	1987	173
4744552	Craftsman's jewelry support tool	—	1986	1988	269
4903784	Impact hammer power tool	—	1988	1990	173
5120657	Apparatus for genetic transformation	Dennis E. McCabe, Brian J. Martinell	1989	1992	435
5125637	Feeding mechanism for newspaper compiler having a movable vacuum valve assembly	—	1991	1992	271
6105955	Feeder structure and receiving wheel for high speed inserter	Greg A. Rawlings, William R. Kline, David D. Rhoads	1998	2000	271

Notes: Patents of Donald A. Glaser with the USPTO from Google Patents.

Table A6. Selection into Winning

	Winning 1950–1974 (1)	First Winning Year (2)
Technology age 1949	0.0010*	0.0275
	(0.0006)	(0.0246)
1943–1949		
Annual patents (thousands)	0.0763	−21.5114*
	(0.3254)	(12.5938)
Government-funded patents (thousands)	−1.8120	−562.4202***
	(5.4728)	(183.6897)
Inventors (thousands)	0.0017	−2.389
	(0.0630)	(1.7261)
Observations	439	105

Notes: Each coefficient and standard error comes form a bivariate regression where the dependent variable is an indicator for winning between 1950 and 1974 (Column 1) or the first year of winning (Column 2).

Table A7. Most Nominated Unsuccessful Nominees

Chemistry		Physics		Medicine	
Christopher Kelk Ingold	117	Arnold Sommerfeld	84	Gaston Ramon	155
Neil Bartlett	71	George E Uhlenbeck	70	Emile P Roux	115
Walter Reppe	64	Samuel A Goudsmit	70	René Leriche	79
Georges Urbain	56	Henri Poincaré	51	Jacques Loeb	78
Henry Eyring	53	N N Bogoljubov	48	Albert Calmette	77
Gilbert N Lewis	41	B B Rossi	47	Rudolf Weigl	74
Klaus Clusius	39	Friedrich Paschen	45	Aldo Castellani	61
Johannes M Bijvoet	36	Y K Zavoisky	41	Charles J Bouchard	57
Friedrich A Paneth	35	Augusto Righi	40	Alfred N Richards	57
Fritz Kögl	35	Robert W Wood	39	Ferdinand Sauerbruch	56

Notes: Names of nominees with the highest number of nominations for the Nobel Prize in Chemistry, Physics, and Medicine who did not win.

Table A8. Winners with Only One Nomination in Winning Years

Chemistry			Physics			Medicine		
laureate	wyear	ntotal	laureate	wyear	ntotal	laureate	wyear	ntotal
Fritz Haber	1918	10	Pieter Zeeman	1902	3	Emil T Kocher	1909	6
Francis W Aston	1922	1	Marie Curie	1903	3	Albrecht Kossel	1910	7
The Svedberg	1926	11	K F Braun	1909	5	Alexis Carrel	1912	3
Arthur Harden	1929	1	J D van der Waals	1910	9	S A S Krogh	1920	3
Friedrich Bergius	1931	2	Wilhelm Wien	1911	9	C E Eijkman	1929	28
Harold C Urey	1934	1	N G Dalén	1912	1	C J F Heymans	1938	8
A F J Butenandt	1939	6	Johannes Stark	1919	11	Gerhard Domagk	1939	9
George de Hevesy	1943	31	C E Guillaume	1920	11	Joseph Erlanger	1944	17
Otto Hahn	1944	23	R A Millikan	1923	19	H S Gasser	1944	18
R L M Synge	1952	3	I I Rabi	1944	21	E B Chain	1945	2
N N Semenov	1956	7	E V Appleton	1947	15	Gerty T Cori	1947	2
C N Hinshelwood	1956	12	I M Frank	1958	2	Max Theiler	1951	4
George Porter	1967	7	I Y Tamm	1958	3			
W H Stein	1972	6	S-I Tomonaga	1965	15			
G Wilkinson	1973	10						

Notes: Names of Nobel Prize winners with only one nomination in the year of the award, denoted by wyear. ntotal denotes the cumulative nominations until the year of winning.

Table A9. Travails of Winning the Nobel Prize

	Physics	Chemistry	Medicine	Total
20th-Century Prizes				
Laureates	150	123	150	423
Mean	15.83	15.74	15.61	15.73
Standard deviation	10.94	10.02	10.04	10.34
Min	1	1	1	1
Max	54	43	56	56
Main Sample (1943–1990)				
Laureates	94	75	107	276
Mean	17.06	16.04	15.72	16.26
Standard deviation	11.31	9.19	10.21	10.32
Min	1	2	1	1
Max	54	38	56	56

Notes: Table A9 reports the lag time (in years) between the completion of prize-winning work and the awarding of the Nobel Prize, for all 20th-century prizes (upper panel) and for the main sample from 1943 to 1990 (lower panel). Data on the timing of the prize-winning work are from Feldman (2000) and Li et al. (2019).

Table A10. N-gram Exclusion Criteria

Criterion	Pattern	Example N-grams
1. Grammatical or Structural Issues	Verb–object or verb–noun	`store_oxygen`, `treat_electrodynamic`
	Adjective–verb or adverb–verb	`tightly_pack`, `strong_oscillating`
	Past participles or descriptive phrases	`thawing_release`, `story_unfold`
	Passive or awkward verb phrases	`acid_be_activate`, `cycle_be_repeat`
	Incomplete or unnatural structures	`material_i_purification`, `body_by_shallow`
2. Ambiguity or Vagueness	Overly general or vague phrases	`unusual_signal`, `output_in_man`
	Context-dependent phrases	`state_charge`, `carrier_of_strong`
3. Typographical or Formatting Errors	Stray numbers or suffixes	`vinyl_polymerizations1`, `appleton1_and_hey2`
	Malformed compound words	`stable_cell_free`, `supernate_fraction`
4. Colloquial or Narrative Language	Narrative or anecdotal expressions	`story_unfold`, `flick_through_nature`
	Colloquial expressions	`unlimited_energy`, `violent_disturbance`
5. Nonstandard or Fabricated Terms	Unrecognized constructs	`symmetrical_sakata`, `convariant_and_practical`
	Incorrect variations	`sulfur_attach`, `albeit_with_infinite`

Notes: This table defines five criteria used to exclude n-grams that do not reflect meaningful scientific concepts. Patterns are categorized based on grammar, ambiguity, typographical errors, informal language, or nonstandard terminology.

Table A11. Other major scientific awards

	Name	Institution	First year	Field
1	Copley Medal	Royal Society of the United Kingdom	1731	any field of science
2	Davy Medal	Royal Society of London	1877	chemistry
3	Lasker Awards	Lasker Foundation	1945	medical science
4	Enrico Fermi Award	Department of Energy	1956	energy
5	Franklin Medal	Franklin Institute	1915	any field of science
6	Hughes Medal	Royal Society of London	1902	physical sciences
7	Max Planck Medal	German Physical Society	1929	theoretical physics
8	Gairdner Foundation International Award	Gairdner Foundation	1959	medical science
9	Faraday Medal	UK Institution of Engineering and Technology	1922	engineering and technology

Notes: This table lists nine major international scientific awards (in addition to the Nobel Prize), together with the name of the awarding institution, the first year of award, and the field of award.

	Sample (1950–1974)		
	Laureates	Non-winning nominees	Difference
Count	65	180	
Number of awards	88	235	
Number of awards per scientist	1.35	1.31	0.04
	(0.08)	(0.05)	(0.10)
Number of awards per scientist			
before the Nobel Prize	1.25		
	(0.09)		
before the first year of nomination		1.20	0.05
		(0.05)	(0.11)
Years between the first award			
and the Nobel Prize	4.47		
	(1.17)		
and the first year of nomination		8.07	−3.60
		(1.22)	(2.77)

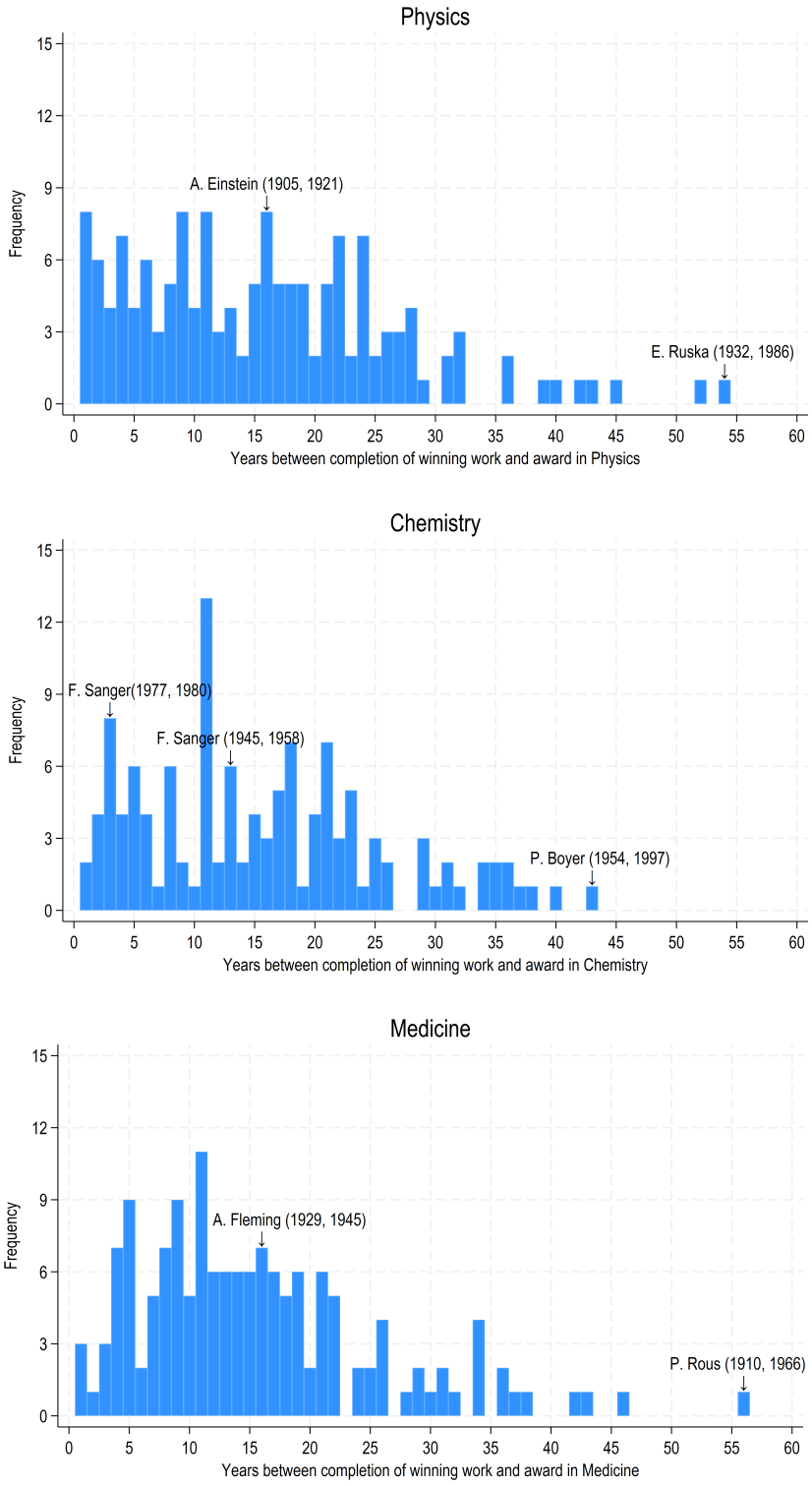
Notes: This table compares the other major awards won by Nobel laureates and non-winning nominees in the main sample. Included are scientists who received at least one of the nine major awards. Standard errors are in parentheses.

Table A12. Distance to winning classes

Distance	USPC	Share (%)	Inventors	Overlap
1	518	64.92	1,770	1,149
2	23	56.32	2,308	1,300
3	216	51.40	9,314	4,787
⋮	⋮	⋮	⋮	⋮
104	182	12.26	14,024	1,720
105	66	11.87	10,016	1,189
106	482	9.45	13,921	1,316

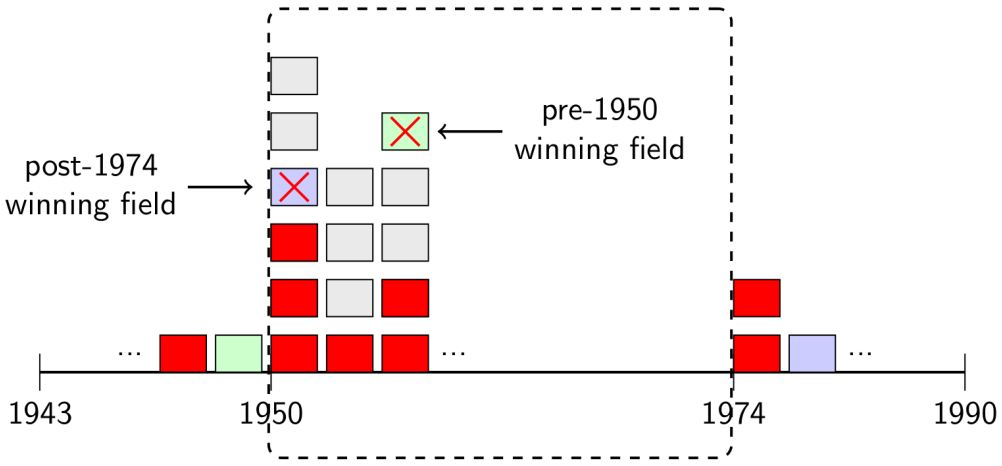
Notes: This table illustrates the ranking of 106 subclasses of the non-winning nominees in terms of the distance to the winning classes. The share denotes the percent of inventors who patented in each subclass who also held at least one patent in the winning classes.

Figure A1. Travails of Winning the Nobel Prize



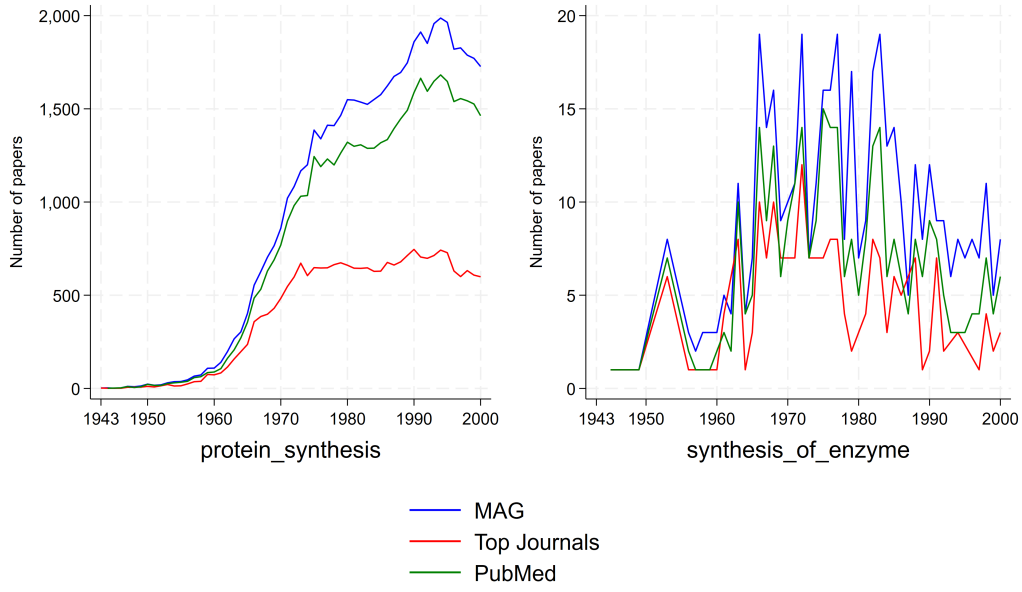
Notes: Distribution of the number of years between the completion of Nobel winning work and the awarding of the Nobel Prize, for prizes award between 1901 and 2000. The pair of years in parentheses indicates the year of the work and the year of the award, respectively. Data on the timing of the winning work are from Feldman (2000) and Li et al. (2019).

Figure A2. Defining Treated and Control



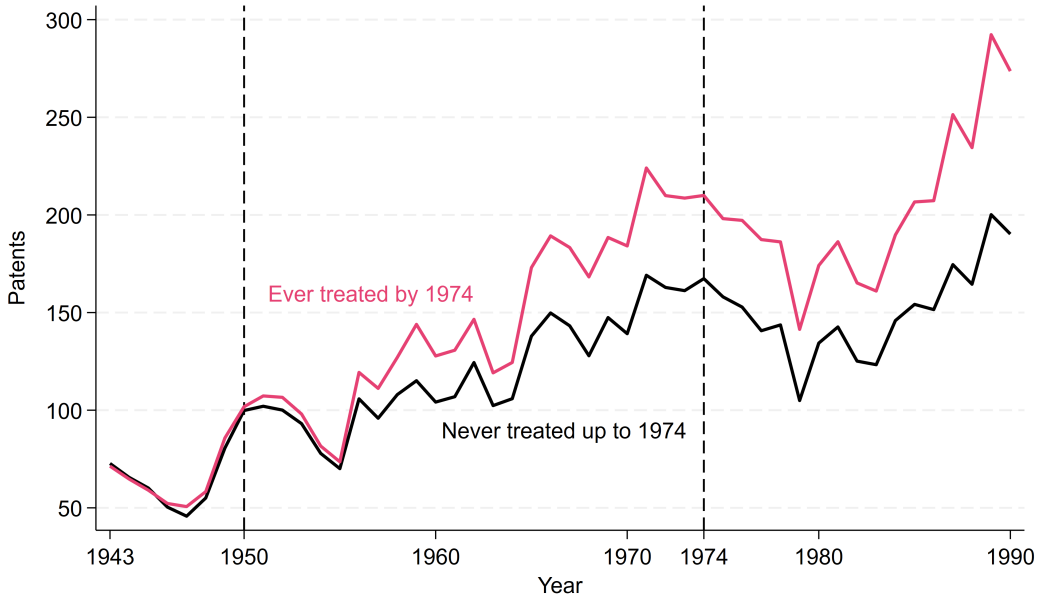
Notes: This figure illustrates the sample selection. Patent classes that won before 1943 or after 1974 are taken out of the sample to ensure clean comparisons.

Figure A3. Comparing MAG and Two Subsamples



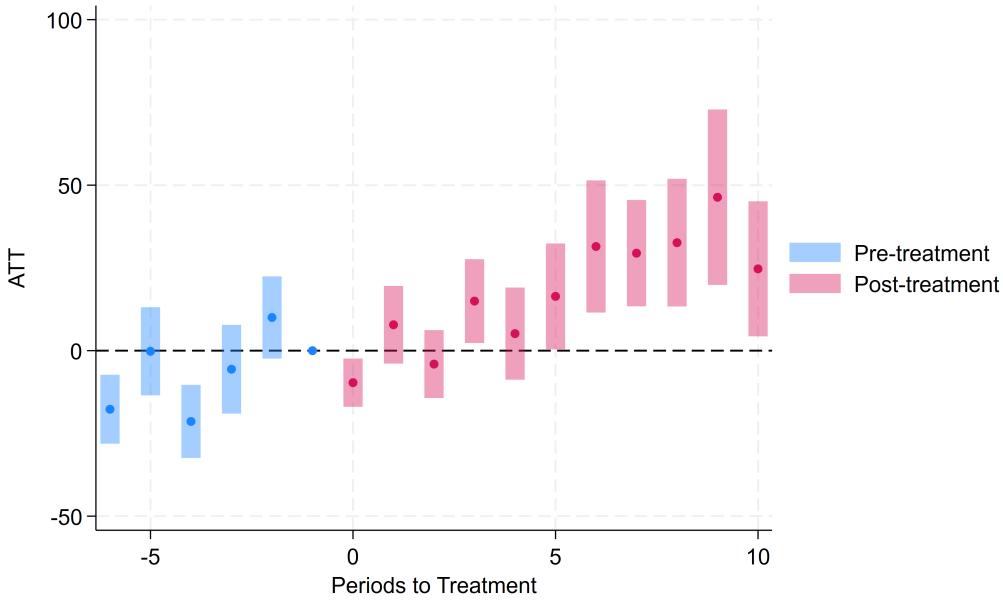
Notes: This figure compares the frequency of the bigram *protein synthesis*(left panel) and the trigram *synthesis of enzyme* (right panel) across three datasets: MAG, top journals, and PubMed.

Figure A4. Treated and Never-Treated



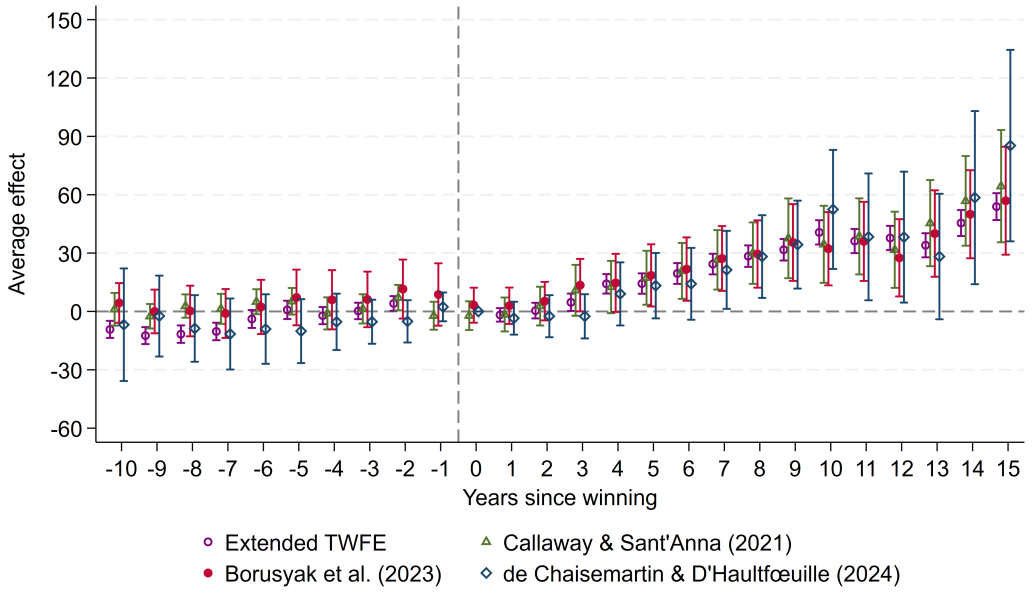
Notes: The red line shows the number of patents per class per year for 105 winning classes between 1950 and 1974. The black line shows the number of patents per class per year for 106 classes of the nominees that never won up to the year 1974.

Figure A5. Spillover for Adjacent Technologies



Notes: This figure compares patenting activities in adjacent winning classes and non-winning classes of the nominees.

Figure A6. Other Estimators



Notes: This figure compares the event study estimates in equation (1) for the number of patents, using four estimators: Wooldridge (2023), Callaway and Sant'Anna (2021), Borusyak et al. (2024), and de Chaisemartin and D'Haultfœuille (2024).

Appendix B. Nomination and Selection Process

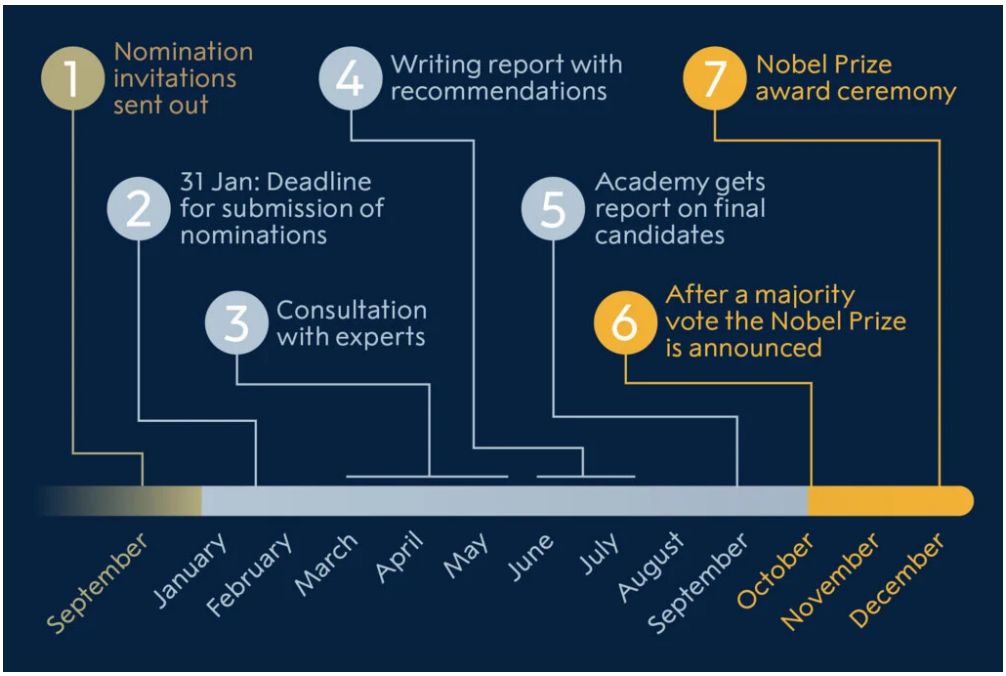
Nominations for the physics and chemistry prizes can be submitted by

(1) Swedish and foreign members of the Royal Swedish Academy of Sciences;
(2) members of the Nobel Committees for Physics and Chemistry;
(3) physics and chemistry Nobel laureates ;
(4) permanent and assistant professor of physics and chemistry in Sweden, Denmark, Finland, Iceland, and Norway;
(5) professors of physics and chemistry in selected schools in other countries (the selection changes from year to year);
(6) other scientists who receive individual invitations to submit nominations.

Nominations for the physiology or medicine prize can be submitted by

(1) members of the Karolinska Assembly, comprising 50 elected members from among the professors of medical subjects at the Karolinska Institute;
(2) Swedish and foreign members of the medical class of the Royal Swedish Academy of Sciences;
(3) Nobel laureates in physiology or medicine;
(4) professors of medicine in Sweden, Denmark, Finland, Iceland, and Norway;
(5) professors of medicine in selected schools in other countries (the selection changes from year to year);
(6) other scientists who receive individual invitations to submit nominations.

Figure B1. Nomination and Selection Timeline



Notes: Nomination and selection of physics laureates. NobelPrize.org. Nobel Prize Outreach 2024. <https://www.nobelprize.org/nomination/physics/>