The Anatomy of a Nobel Prize:
Evidence from Economics Laureates (1969–2025)

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Abstract

What happens when an economist wins the Nobel Prize? Using novel data on all 99 laureates (1969–2025), I document five facts about paths to Stockholm: the PhD-to-Nobel gap has remained stable at 39 years despite dramatic changes in the profession; 24% of laureates trained under previous Nobel winners; productivity follows a lifecycle pattern that peaks decades before recognition; collaboration has shifted from 77% solo authorship in the 1960s to 15% by 2020; and future Nobel winners are indistinguishable from non-winners among Clark Medal recipients. Exploiting the Clark Medal comparison in a difference-in-differences design, I find the Nobel generates a 25–30% citation boost to prior work—an effect that builds over time and concentrates on "canonical" papers cited in the prize announcement. Despite this external validation, the prize has no detectable effect on productivity or collaboration: by age 67, research patterns are established. The Nobel amplifies specific ideas rather than conferring a diffuse halo.

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1 Introduction

The Nobel Prize in Economics was never supposed to exist. When Alfred Nobel drafted his will in 1895, he established prizes for physics, chemistry, medicine, literature, and peace—but not economics. The economics prize was created seventy-three years later by Sweden's central bank, the Sveriges Riksbank, on its 300th anniversary. Officially titled the "Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel," it was first awarded in 1969 to Ragnar Frisch and Jan Tinbergen for their pioneering work in econometrics. Members of the Nobel family have objected to the association. Peter Nobel, Alfred's great-great-nephew, called it "a PR coup by economists to improve their reputation," and in 2001, four family members published a letter in *Svenska Dagbladet* arguing that the economics prize "degrades and cheapens the real Nobel Prizes." Yet no award in the social sciences commands comparable prestige, and none shapes careers and public discourse as profoundly.

Not everyone within the profession has welcomed this development. When Friedrich Hayek accepted the prize in 1974—sharing it, ironically, with Gunnar Myrdal, his ideological opposite—he used his banquet speech to argue the prize should never have been created. "The Nobel Prize confers on an individual an authority which in economics no man ought to possess," Hayek warned. Unlike in the natural sciences, where "fellow experts will soon cut him down to size if he exceeds his competence," the economist's influence extends to "laymen: politicians, journalists, civil servants and the public generally." Hayek worried that laureates would be treated as "omnicompetent on all problems of society" and eventually "persuaded to believe" it themselves. He concluded by quoting Alfred Marshall: "Students of social science must fear popular approval: Evil is with them when all men speak well of them."

Hayek's concerns raise empirical questions that have received surprisingly little systematic attention. What happens when an economist wins the Nobel Prize? Does it amplify their influence, as Hayek feared? Does it change how they work? And which of their ideas benefit from the spotlight? These questions matter not only for understanding scientific recognition

but also for assessing whether the profession's highest honor serves its intended purpose of rewarding contributions that, in Nobel's words, "confer the greatest benefit to humankind."

The 99 economists who have received the prize since 1969 constitute an extraordinarily select group. They span the discipline's methodological traditions—from the mathematical general equilibrium theory of Kenneth Arrow to the field experiments of Esther Duflo, from the monetarism of Milton Friedman to the behavioral economics of Daniel Kahneman. The youngest laureate, Duflo, was 47 when she won in 2019; the oldest, Leonid Hurwicz, was 90 when he received the prize in 2007 and passed away just five months later. Only three women have ever won: Elinor Ostrom (2009), Duflo (2019), and Claudia Goldin (2023)—representing just 3% of all laureates. The median laureate waits 39 years from PhD to Nobel, and 24% were trained by a previous Nobel laureate—suggesting that intellectual dynasties play a substantial role in producing future winners.

This paper provides the first comprehensive empirical analysis of Nobel laureates in economics. We ask three questions. First, what characterizes the careers of Nobel laureates? We document patterns in training, productivity, collaboration, and the remarkable concentration of talent at a handful of elite institutions. Second, does winning the Nobel Prize *cause* changes in how laureates' work is received and how they conduct research? We use difference-in-differences methods with John Bates Clark Medal winners as a comparison group to estimate causal effects on citations and collaboration. Third, which papers benefit from the Nobel halo? We distinguish between "canonical" papers—those explicitly cited in the Nobel announcement—and the laureate's broader portfolio to identify where the citation boost concentrates.

To answer these questions, we construct a novel dataset covering all 99 Nobel laureates from 1969 to 2025. We combine multiple sources: biographical information from the Nobel Prize website and laureate autobiographies; complete publication records from the Research Papers in Economics (RePEc) database, yielding 13,817 unique publications after deduplication; annual citation counts from OpenAlex for 12,022 matched publications; and

hand-collected data on doctoral training, including PhD institution, graduation year, and advisor for 95 of 98 laureates with doctoral degrees. We supplement this with comparable data on all 44 John Bates Clark Medal winners (1947–2025), 13 of whom subsequently won the Nobel Prize.

The Clark Medal provides an ideal comparison group for causal inference. Awarded by the American Economic Association to the most accomplished American economist under 40, it identifies researchers at the frontier of the profession before Nobel selection. At the time of their Clark Medal, future Nobel winners and non-winners are statistically indistinguishable on observable characteristics: publications, Top 5 placements, solo authorship rates, and team size all show no significant differences. This balance supports our identifying assumption that, conditional on receiving the Clark Medal, subsequent Nobel selection is orthogonal to pre-existing research trajectories.

We document five stylized facts about laureate careers. First, the path to Stockholm takes four decades: the median gap from PhD to Nobel is 39 years, with remarkable stability across cohorts despite dramatic changes in the profession. Second, intellectual dynasties dominate: 24% of laureates were supervised by someone who had already won the Nobel. The Arrow dynasty alone spans three generations and seven laureates; the Leontief-Solow lineage produced six. Third, productivity declines and stagnates after the prize, continuing a lifecycle pattern already underway—but whether this reflects a causal "Nobel curse" or simply career aging cannot be determined without a comparison group. Fourth, collaboration has increased dramatically: solo authorship fell from 77% of papers in the 1960s to just 15% by 2020, mirroring profession-wide trends. Fifth, among Clark Medal winners, those who eventually win the Nobel are indistinguishable ex ante from those who do not, supporting the validity of our research design.

Our causal estimates reveal two main findings. First, the Nobel Prize generates a substantial and sustained citation boost. Papers by Nobel laureates receive 25–30% more annual citations after the prize announcement relative to papers by Clark medalists who did not

win. This effect builds over time, starting at roughly 8% in the announcement year and rising to 36% by eight years post-Nobel. Second, the prize has no detectable effect on collaboration patterns. Point estimates for team size are small, inconsistent across specifications, and statistically insignificant. By the time economists win the Nobel—typically in their late 60s, after four decades of research—their production mode is well-established.

Perhaps our most novel finding concerns *which* papers benefit from the Nobel halo. We show that the citation boost concentrates heavily on canonical papers—those explicitly cited in the Nobel announcement—rather than spreading across the laureate's entire portfolio. Canonical papers receive an additional 20–25% citation increase relative to the laureate's non-canonical work, and this differential grows over time. This pattern clarifies the mechanism behind the Nobel effect: the prize directs attention to specific contributions rather than generating a diffuse increase in the laureate's visibility. The Nobel committee, in effect, curates which ideas receive amplified attention.

This paper contributes to several literatures. Most directly, we extend the pioneering work of Zuckerman (1977) on scientific elites to economics, providing comprehensive descriptive statistics that update her analysis of American Nobel laureates through 1972. Our causal estimates complement Borjas and Doran (2015) on the Fields Medal in mathematics and Bhattacharya et al. (2023) on the Nobel in physiology and medicine, both of which document post-prize productivity declines. Our distinction between canonical and non-canonical papers contributes to the literature on citation dynamics and the Matthew effect (Merton, 1968, 1988), showing that recognition effects are targeted rather than diffuse. Finally, our documentation of intellectual dynasties extends Tol (2018) network analysis with complete genealogical data and visualization of advisor-student chains.

The paper proceeds as follows. Section 2 reviews related literature on Nobel effects, cumulative advantage, and intellectual dynasties. Section 3 describes our data sources and sample construction. Section 4 documents five descriptive facts about laureate careers. Section 5 presents our empirical strategy, including the difference-in-differences design and identifying

assumptions. Section 6 reports causal estimates for citations and collaboration, including the canonical versus non-canonical decomposition. Section 7 concludes with implications for understanding scientific recognition and directions for future research.

2 Related Literature

This paper contributes to several interrelated literatures on the economics and sociology of science: the effects of prizes and recognition on scientific productivity, the Matthew effect and cumulative advantage, intellectual dynasties and knowledge transmission, and the lifecycle of scientific creativity.

2.1 The Nobel Prize Effect

The seminal work on Nobel laureates remains Zuckerman (1977), whose *Scientific Elite* tracked all American laureates from 1907 to 1972 through biographical data and interviews with 41 living laureates. Zuckerman documented how laureates are "successively advantaged as time passes," finding that these cumulative advantages produce growing disparities between the elite and other scientists. Her work introduced the concept of "accumulation of advantage" to the study of scientific careers, showing how early success compounds into later recognition.

Subsequent research has examined how the Nobel Prize itself affects laureates' subsequent productivity, with mixed findings. Borjas and Doran (2015) study the Fields Medal in mathematics—often called the "Nobel of mathematics"—and find that recipients' productivity *declines* after the award. Medalists "play the field," exploring unfamiliar topics at the expense of writing papers, with about half of the productivity decline attributable to this increased cognitive mobility. Bhattacharya et al. (2023) compare Nobel laureates in physiology and medicine (1950–2010) with matched Lasker Award winners and find that pre-Nobel, laureates' publications were more voluminous, highly cited, and novel. Post-Nobel, laureates'

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productivity decreased sharply, eventually falling below that of Lasker winners on all three measures—driven largely by the "diversionary effects" of becoming public intellectuals rather than focusing on original research. The evidence on citation effects is more robust. Farys and Wolbring (2017) and others find significant citation boosts to laureates' papers after the prize, though the mechanisms remain debated. Frandsen and Nicolaisen (2013) document a "ripple effect" whereby Nobel recognition generates citation chain reactions extending to papers the laureate has cited. Our finding that the citation boost concentrates on canonical papers rather than spreading across the laureate's portfolio contributes to this debate by clarifying *which* papers benefit.

2.2 The Matthew Effect and Cumulative Advantage

Merton (1968) introduced the Matthew effect—named for the Gospel according to St. Matthew ("For unto every one that hath shall be given")—to describe how eminent scientists receive disproportionate credit for contributions. In his follow-up (Merton, 1988), Merton developed the concept of cumulative advantage, whereby early success generates opportunities that compound into further success. Interviews with laureates consistently revealed how recognition flows to already-recognized scientists: as Merton noted, the same discovery might be attributed to the famous collaborator rather than the unknown contributor.

The Matthew effect has been documented at multiple levels of scientific hierarchy. Larivière and Gingras (2010) show that papers in high-impact journals receive twice as many citations as identical papers published elsewhere. Recent work by Azoulay et al. (2014) finds that positive status shocks in mid-career significantly boost subsequent citation impacts and funding success. Our results on intellectual dynasties extend this logic intergenerationally: laureates who trained under laureates benefit from both knowledge transmission and the reflected prestige of their advisors.

2.3 Intellectual Dynasties and Knowledge Transmission

The concentration of Nobel Prizes within academic lineages has long intrigued scholars. Zuckerman (1977) documented that a disproportionate share of laureates trained under previous laureates, introducing the concept of "masters and apprentices" in science. She found that laureate advisors—whom Merton (1960) called "evokers of excellence"—helped students identify "big" problems and provided privileged access to resources and recognition.

Tol (2018) maps the complete professor-student network of economics Nobel laureates, finding that laureates cluster into connected components with Harvard and Chicago as central nodes. His analysis shows that 24 of 47 likely candidates for future Nobel Prizes have a Nobel ancestor in their academic genealogy. Rosenstreich et al. (2017) use network analysis to demonstrate that Nobel laureate mentoring patterns are non-random, with subnetworks of laureates extending across four generations. These "successful mentoring communities" centered historically on Cambridge (late 19th century) and Columbia (early 20th century), reflecting how intellectual influence accumulates within institutions.

Our documentation of dynasties like Leontief's (11 laureates across three generations) and Arrow's (8 laureates including grandstudents Tirole, Banerjee, and Aghion) extends this literature with comprehensive data on the economics prize. Whether these patterns reflect knowledge transmission, selection, or committee preferences remains an open question we discuss but cannot definitively resolve.

2.4 The Lifecycle of Scientific Creativity

When do scientists produce their best work? Jones and Weinberg (2011) analyze Nobel laureates across physics, chemistry, and medicine, finding dramatic shifts in the age of prize-winning work over the 20th century. The mean age increased by 13.4 years in physics, 10.2 in chemistry, and 7.4 in medicine between the early (before 1905) and late (after 1985) periods. Before 1905, 60% of physics laureates made their contributions before age 40; since 2000, only 19% have done so.

Weinberg and Galenson (2019) distinguish between "conceptual" and "experimental" innovators among economics laureates. Conceptual innovators—who challenge conventional wisdom with sudden new ideas—peak around age 25–32. Experimental innovators—who accumulate knowledge and find new ways to synthesize information—peak in their mid-50s. The 20-year gap between these peaks explains much of the variance in the age-creativity relationship.

These findings help interpret our results on PhD-to-Nobel lag. The median lag of 39 years in our data reflects both the time required for contributions to be recognized and validated, and the growing complexity of economics that pushes prize-winning work later in careers. The Nobel committee's preference for honoring contributions whose impact has been demonstrated over decades creates a systematic "backlog" of award-worthy candidates.

2.5   The John Bates Clark Medal as Comparison

The John Bates Clark Medal, awarded to American economists under 40, provides a useful comparison to the Nobel. Chan et al. (2013) examine whether the Clark Medal boosts subsequent productivity and citations, finding modest positive effects. Cherrier and Svorenčík (2020) trace the medal's 70-year history, documenting how definitions of "excellence" have shifted from theoretical to empirical work and how laureates have concentrated at Harvard, MIT, and Chicago.

The Clark Medal's strong predictive power for the Nobel—roughly 40% of Clark medalists eventually win—makes it a natural control group for isolating Nobel-specific effects. Our use of Clark medalists as a comparison group follows this logic: both groups represent the elite of the profession, but only Nobel laureates experience the global recognition and "minor celebrity" status that accompanies the prize.

2.6 Contributions of This Paper

Our paper contributes to this literature in several ways. First, we provide comprehensive descriptive statistics on all 96 economics Nobel laureates (1969–2025), documenting patterns in training, productivity, and collaboration that update and extend Zuckerman's analysis to economics. Second, we use modern causal inference methods—difference-in-differences with event studies and synthetic control groups—to identify Nobel effects on citations and collaboration, providing more rigorous estimates than previous correlational studies. Third, our distinction between canonical and non-canonical papers clarifies the mechanism behind citation effects: the Nobel directs attention to specific contributions rather than generating a general "halo effect." Finally, our documentation of intellectual dynasties with complete genealogical data and visualizations contributes to understanding knowledge transmission in economics.

3 Data

We construct a novel dataset covering the universe of Nobel Memorial Prize laureates in Economic Sciences from the prize's inception in 1969 through 2025. This section describes our data sources and sample construction; Section 4 documents descriptive patterns and Section 6 presents causal estimates.

3.1 Nobel Laureate Sample

Our sample consists of all 99 individuals who received the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel between 1969 and 2025.[1] Biographical information—including birth year, nationality, gender, and institutional affiliation at the time of the award—was collected from the official Nobel Prize website (`https://www.`

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[1]We exclude the 2025 laureates from analyses requiring post-Nobel outcomes due to insufficient observation time.

`nobelprize.org`) and verified against laureates' Wikipedia pages and university biographies.

Table 1 presents summary statistics. Panel A summarizes biographical characteristics. Laureates were born between 1895 (Ragnar Frisch) and 1972 (Esther Duflo), with a mean birth year of 1933. The average age at the time of the Nobel Prize is 67 years, ranging from 47 (Esther Duflo, 1972) to 90 (Leonid Hurwicz, 2007). The gender composition is heavily skewed: only 3.0% of laureates are female—Elinor Ostrom (2009), Esther Duflo (2019), and Claudia Goldin (2023). As of December 2025, approximately half (52%) of all laureates remain alive.

Panel B describes doctoral training. Among the 98 laureates with doctoral degrees, the average PhD completion year is 1961, with laureates typically completing their degrees at age 28. The concentration of training in U.S. institutions is striking: 76% of laureates earned their PhD from an American university, and 55% graduated from one of six elite institutions (MIT, Harvard, Chicago, Princeton, Yale, or Stanford).

Table 1: Summary Statistics: Nobel Laureate Characteristics

Variable	N	Mean	SD	Min	Max
Panel A: Biographical					
Birth year	99	1933.1	18.40	1895	1972
Nobel year	99	2000.1	16.69	1969	2025
Age at Nobel	99	67.01	8.30	47	90
Female	99	0.030	0.17	0	1
Currently alive	99	0.515	0.50	0	1
Panel B: PhD Training					
PhD year	98	1961.1	18.14	1923	1999
Years PhD to Nobel	98	39.00	7.86	20	59
Age at PhD	98	27.78	3.92	22	44
US PhD	99	0.758	0.43	0	1
Elite PhD	99	0.545	0.50	0	1

Notes: Sample includes all 99 Economics Nobel laureates, 1969–2025. N=98 for PhD-related variables excludes Leonid Hurwicz, who completed an LL.M. (Warsaw, 1938) but never earned a doctoral degree. Elite PhD institutions: MIT, Harvard, Chicago, Princeton, Yale, Stanford.

3.2 Publication Records

We collected complete publication histories for each laureate from the Research Papers in Economics (RePEc) database, accessed via IDEAS (`https://ideas.repec.org`). RePEc is the most comprehensive bibliographic database for economics research, covering over 4.4 million items from 3,600 journals and 5,600 working paper series.

For each laureate, we scraped their complete publication list from their RePEc author page, extracting: publication title, year, venue (journal or working paper series), publication

type, and co-author information. The scraping was conducted in November 2025.

The raw extraction yielded 32,638 records. However, RePEc catalogues the same research output multiple times when it appears in different venues—for instance, a paper first circulated as an NBER Working Paper and later published in the *American Economic Review* generates separate entries. We deduplicated records by matching on laureate name and normalized title, retaining a single entry per unique paper. This procedure reduced the dataset to 13,817 unique publications.

Table 2 presents summary statistics. The median laureate has 121 publications, with substantial variation ranging from 11 (John Nash) to 706 (Joseph Stiglitz). Of published articles with identifiable venues, 23.8% appeared in Top 5 journals (AER, Econometrica, JPE, QJE, REStud). The average solo-authorship rate is 54%, though this varies considerably across cohorts—earlier laureates such as Vickrey (95%), Schultz (94%), and Hicks (93%) worked predominantly alone, while recent laureates increasingly collaborate.

Table 2: Summary Statistics: Publication Records

Variable	N	Mean	SD	Min	Max
Panel A: Publication Counts (per laureate)					
Total publications	99	139.6	106.7	11	706
Pre-Nobel publications	99	91.6	80.8	1	455
Post-Nobel publications	99	48.0	60.5	0	390
Top 5 journal articles	99	33.2	27.4	2	150
Panel B: Collaboration					
Solo-authored share	99	0.539	0.24	0.00	0.95
Average co-authors	99	1.77	0.46	1.05	3.20
Panel C: Career Characteristics					
Career length (years)	99	57.2	14.5	28	96

Notes: Publication data from RePEc/IDEAS, collected November 2025. Raw data (32,638 records) deduplicated to 13,817 unique publications. Career length defined as years between first and last publication. Top 5 journals: AER, Econometrica, JPE, QJE, REStud. Most prolific: Stiglitz (706), Heckman (489), Acemoglu (482). Highest solo-authorship rates: Vickrey (95.3%), Schultz (93.8%), Hicks (93.2%).

Figure 1 visualizes these patterns. Panel (a) confirms that working papers dominate the publication mix, reflecting both their importance in economics research dissemination and RePEc's comprehensive coverage of working paper series. Panel (b) ranks journals by laureate publications, with the American Economic Review leading substantially. Panel (c) displays the right-skewed distribution of total output, and Panel (d) reveals strong persistence in productivity—laureates who published extensively before the prize generally continued to do so afterward.
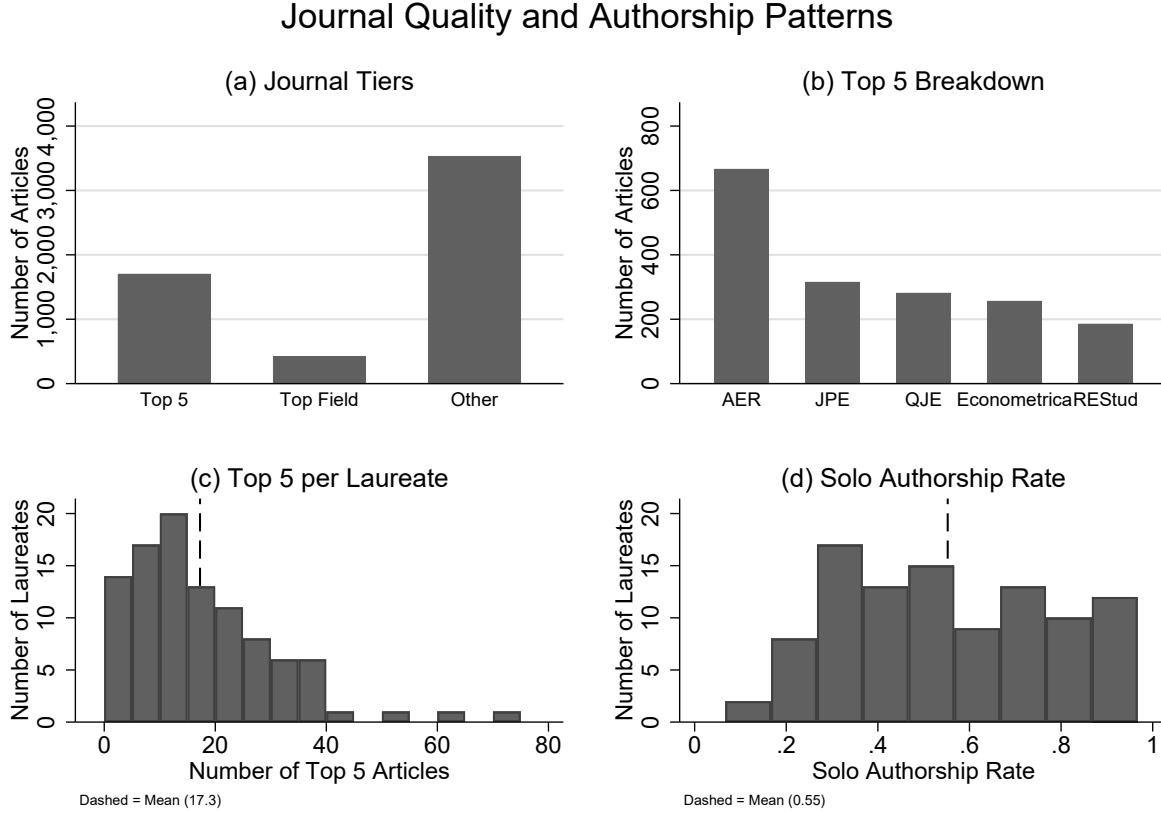
Publication Patterns of Nobel Laureates in Economics

(a) Publication Types

(b) Top 10 Journals

(c) Publications per Laureate

Dashed = Mean, Dotted = Median

(d) Pre vs Post Nobel
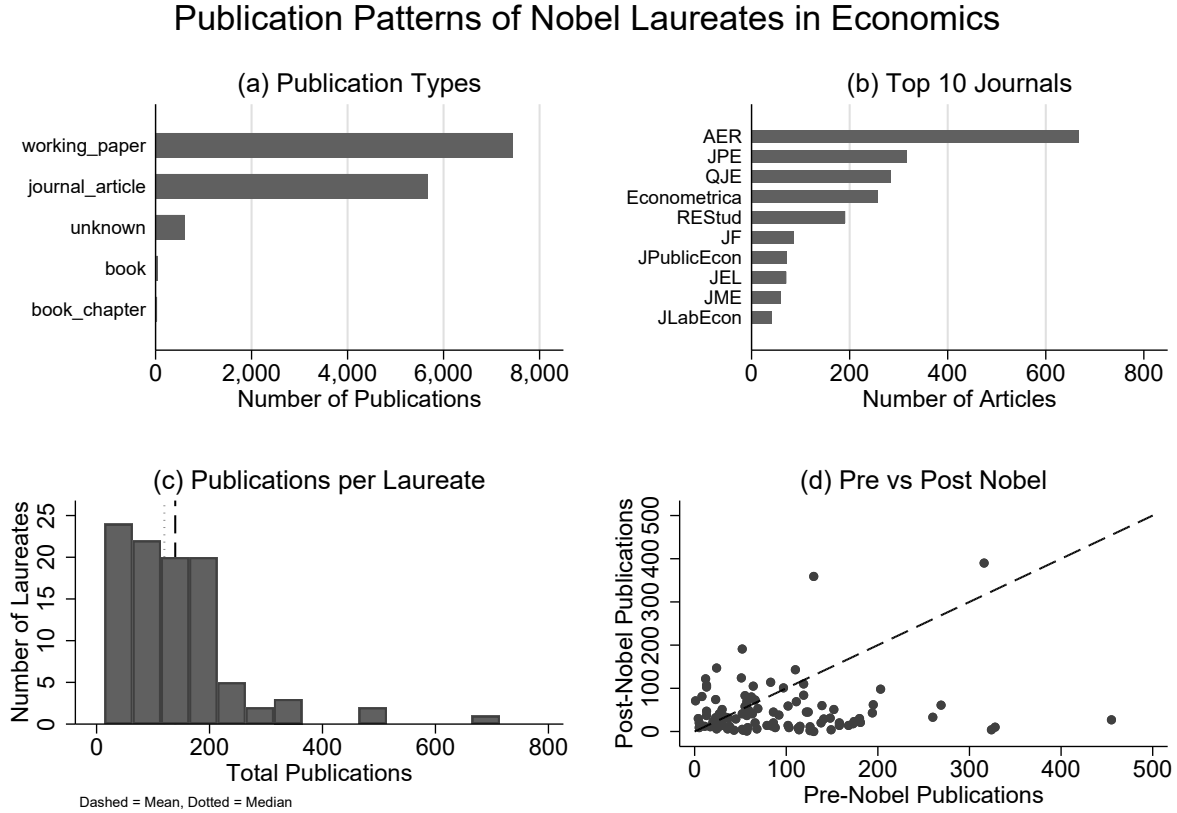
Source: RePEc/IDEAS. N = 13,791 publications across 99 laureates (1969-2025).

Figure 1: Publication Patterns of Nobel Laureates

Notes: Panel (a) shows distribution across publication types. Panel (b) ranks journals by laureate publications. Panel (c) displays total publications per laureate (dashed = mean, dotted = median). Panel (d) plots pre-Nobel against post-Nobel counts. Source: RePEc/IDEAS. N = 13,791 publications across 99 laureates (1969–2025).

Figure 2 examines publication quality and collaboration. Panel (a) classifies journal articles by tier: 1,706 appeared in Top 5 journals, 423 in top field journals, and 3,533 in other outlets. Panel (b) disaggregates Top 5 publications by journal. Panel (c) shows the distribution of Top 5 articles per laureate—the mean of 17.3 masks substantial heterogeneity, with some laureates exceeding 60 Top 5 publications while others have fewer than 5. Panel (d) documents the solo-authorship distribution; the mean of 55% reflects a mix of earlier laureates who worked predominantly alone and recent laureates who collaborate extensively.

Journal Quality and Authorship Patterns

(a) Journal Tiers
(b) Top 5 Breakdown
(c) Top 5 per Laureate
Dashed = Mean (17.3)
(d) Solo Authorship Rate
Dashed = Mean (0.55)

Source: RePEc/IDEAS. N = 99 laureates (1969-2025).

Figure 2: Journal Quality and Authorship Patterns

Notes: Panel (a) classifies journal articles by tier. Panel (b) shows Top 5 breakdown by journal. Panel (c) displays Top 5 publications per laureate (dashed = mean of 17.3). Panel (d) shows solo-authorship rates (dashed = mean of 0.55). N = 99 laureates (1969–2025).

3.3 PhD Training and Geographic Flows

We manually collected doctoral training information for each laureate, including: PhD-granting institution, graduation year, doctoral advisor(s), birth country, and institutional affiliation at the time of the award. Primary sources included laureate autobiographies on the Nobel Prize website, university archives, Wikipedia, and the Mathematics Genealogy Project.

Figure A6 presents the complete geographic trajectory of Economics Nobel laureates from birth country through doctoral training to institutional affiliation at the time of award. The

Sankey diagram reveals several patterns.

US dominance persists at every stage: 55% of laureates were born in the US, and US institutions trained 73% of all PhDs and employed 76% at the time of award. This dominance reflects substantial brain drain to the US—international laureates overwhelmingly migrated to US institutions for both doctoral training and careers. Of 43 foreign-born laureates, 35 (81%) received their Nobel while at a US institution.

Table 3 summarizes both PhD training and institutional affiliations at the time of the award. MIT (15), Harvard (14), and Chicago (10) are the top three PhD-granting institutions, together accounting for 39% of all laureates. The top 10 institutions granted PhDs to 73% of laureates, revealing extreme concentration in doctoral training. Only 31 distinct institutions produced all 98 laureates with formal doctorates.

Comparing PhD origins with Nobel affiliations reveals systematic talent flows. Chicago is the largest net importer (+5), training 10 but employing 15 at the time of award. Harvard and MIT are net exporters: Harvard trained 14 but employed 8 (−6), while MIT trained 15 but employed 10 (−5). UC Berkeley is a substantial importer (+5), employing 7 laureates while training only 2 in our sample. The London School of Economics shows the opposite pattern: training 4 laureates but retaining only 1 at the time of award (−3).

We identified doctoral advisors for 95 of 98 laureates with formal PhDs (97%). The resulting network reveals striking patterns of intellectual inheritance: 24 laureates (24%) were supervised by an individual who had already received the Nobel Prize at the time of the student's award. This dynastic pattern—with prominent "Nobel trees" rooted in Kenneth Arrow (4 students), Robert Solow (4 students), Eric Maskin (2 students), and Simon Kuznets (2 students)—suggests that proximity to exceptional scholars during doctoral training substantially increases the probability of future recognition.

Table 3: PhD Training and Nobel Affiliation: Top Institutions

Institution	PhD Training		Affiliation at Award		
	Laureates	Share (%)	Laureates	Share (%)	Net Flow
MIT	15	15.2	10	10.1	−5
Harvard University	14	14.1	8	8.1	−6
University of Chicago	10	10.1	15	15.2	+5
Princeton University	6	6.1	6	6.1	0
Yale University	5	5.1	4	4.0	−1
University of Cambridge	5	5.1	3	3.0	−2
Stanford University	4	4.0	5	5.1	+1
Columbia University	4	4.0	4	4.0	0
London School of Economics	4	4.0	1	1.0	−3
Carnegie Mellon University	4	4.0	2	2.0	−2
UC Berkeley	2	2.0	7	7.1	+5

Notes: Net Flow = Laureates at award − PhDs trained. Positive values indicate net importers of talent; negative values indicate net exporters. PhD institution identified for 98 of 99 laureates; Leonid Hurwicz never earned a doctoral degree. Institutions ordered by PhD training count.

3.4 John Bates Clark Medal Winners

A key challenge in studying Nobel laureates is the absence of an obvious comparison group. We address this by collecting data on all 44 recipients of the John Bates Clark Medal (1947–2025), awarded by the American Economic Association to the most accomplished American economist under age 40.

The Clark Medal provides an ideal comparison group for several reasons. First, it identifies economists at the frontier of the profession early in their careers, before Nobel selection.

Second, Clark medalists share observable characteristics with Nobel laureates: elite institutions, high productivity, and methodological innovation. Third, the strict age cutoff (under 40) creates useful variation in career stage at recognition.

Of the 44 medalists, 13 subsequently won the Nobel Prize, with a median gap of 22 years between awards. The remaining 31 medalists serve as a "near-miss" control group—economists who achieved the highest early-career recognition but were not selected for the Nobel. For Clark medalists, we collected complete publication records from RePEc (13,743 publications) and citation data from OpenAlex (11,489 matched publications).

3.5   Citation Data

To measure research impact, we collected citation data from OpenAlex (`https://openalex.org`), an open catalog indexing over 250 million publications with citation links. For each publication in our RePEc dataset, we queried the OpenAlex API using title matching. We successfully matched 12,022 Nobel laureate publications (90.3%) and 11,489 Clark medalist publications (83.6%) to OpenAlex records.

For matched publications, we retrieved annual citation counts, enabling construction of citation panels. The Nobel laureate citation panel contains 174,394 paper-year observations; the Clark medalist panel contains 156,277 paper-year observations.

3.6   Data Limitations

Several limitations warrant discussion. First, RePEc coverage is incomplete for older publications and non-English journals, potentially undercounting the output of earlier laureates. Second, citation data from OpenAlex may undercount citations from sources not indexed in the database. Third, our advisor identifications rely on secondary sources and may contain errors, particularly for European laureates trained before formal PhD programs were standardized. Despite these limitations, our dataset represents the most comprehensive compilation of Nobel economist careers to date.

4   Descriptive Facts

This section documents five stylized facts about Nobel laureates' careers. We defer causal analysis to Sections 5–6.

4.1   Fact 1: The Path to Stockholm Takes Four Decades

The typical laureate wins the Nobel Prize 39 years after completing their PhD. This lengthy gap has remained remarkably stable across the prize's 56-year history: Figure 3 plots years from PhD to Nobel against the year of the award, revealing no secular trend ($\beta = 0.02$, $p = 0.64$). Decade averages range narrowly from 36 to 41 years. Despite dramatic changes in the profession—the rise of empirical methods, computational economics, and team science— the recognition lag has held steady at approximately four decades.

This stability suggests that the Nobel committee rewards contributions whose influence becomes apparent only over extended periods, not recent breakthroughs. The lag also implies substantial survivor bias: economists must remain alive and productive long enough for their early contributions to be recognized. The minimum gap of 20 years (Esther Duflo, 2019) is itself substantial, and her award was widely viewed as exceptionally rapid.
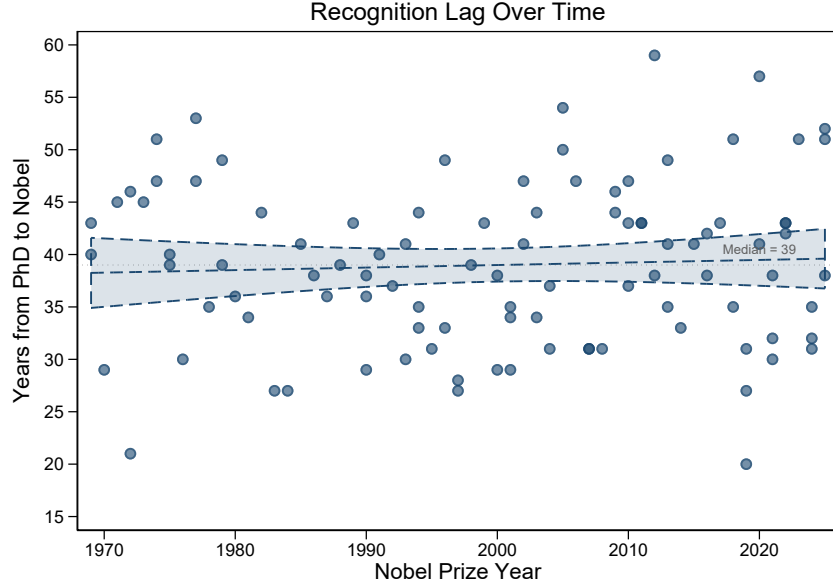
Figure 3: Stability of the PhD-to-Nobel Gap Over Time

Notes: Each point represents one laureate. Horizontal axis shows Nobel Prize year; vertical axis shows years elapsed from PhD completion to Nobel Prize. Dashed line shows linear fit ($\beta = 0.02$, $p = 0.64$); shaded area shows 95% confidence interval. Dotted horizontal line marks the median of 39 years. The flat trend indicates the recognition lag has remained stable despite changes in the profession. $N = 98$ laureates with doctoral degrees.

Does high productivity accelerate recognition? Figure 4 suggests yes: there is a negative correlation between total publications and years from PhD to Nobel. More prolific researchers tend to win sooner. However, selection effects complicate interpretation—researchers who win quickly mechanically have less time to accumulate publications before the prize.
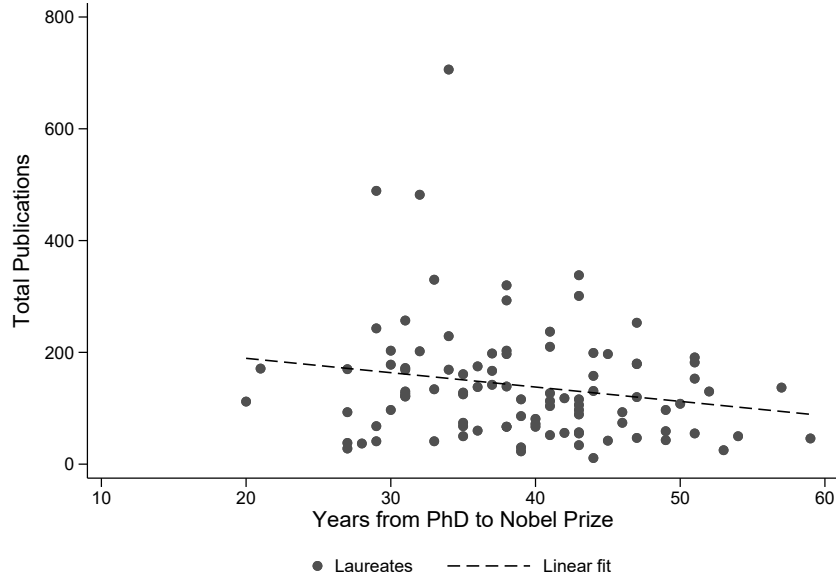
Figure 4: Publications and Time to Nobel Prize

Notes: Each point represents one laureate. Horizontal axis shows years from PhD to Nobel; vertical axis shows total publications. The negative correlation suggests more prolific researchers win sooner, though truncation effects may contribute. $N = 98$ laureates with doctoral degrees.

4.2 Fact 2: Intellectual Dynasties Dominate

Of the 95 laureates with identified doctoral advisors, 24 (24%) were supervised by someone who had already received the Nobel Prize at the time of the student's award.[2] Table 4 lists the most prolific "Nobel advisors," and Figure 5 visualizes the five largest intellectual dynasties.

The Arrow dynasty is the largest in economics. Kenneth Arrow (Nobel 1972) supervised four future laureates: John Harsanyi (1994), Michael Spence (2001), Eric Maskin (2007), and Roger Myerson (2007). Maskin has since produced two Nobel students of his own—Jean Tirole (2014) and Abhijit Banerjee (2019)—creating a three-generation chain of seven

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[2]This definition requires temporal precedence: the advisor must have won *before* the student. An additional 11 laureates were supervised by individuals who would later receive the Nobel Prize, but we exclude these from our primary count since future prizes could not have influenced the student's training environment.

laureates. This dynasty demonstrates how intellectual influence compounds across decades: ideas in general equilibrium, mechanism design, and contract theory flow from Arrow through Maskin to applications in industrial organization and development economics.

The Leontief-Solow lineage rivals Arrow's in influence. Wassily Leontief (Nobel 1973) supervised Robert Solow (1987), who in turn trained an extraordinary cohort at MIT: Joseph Stiglitz (2001), George Akerlof (2001), Peter Diamond (2010), and William Nordhaus (2018). This dynasty of six laureates spans macroeconomics, information economics, public finance, and environmental economics—illustrating how a single methodological tradition (growth accounting, dynamic optimization) can seed diverse research programs.

The Kuznets dynasty connects development economics to finance through an unexpected path. Simon Kuznets (Nobel 1971) supervised both Milton Friedman (1976) and Robert Fogel (1993). Friedman then trained Harry Markowitz (1990), whose portfolio theory revolutionized finance. This four-laureate chain—from development curves to monetarism to modern portfolio theory—shows how intellectual lineages can span seemingly unrelated subfields.

Two smaller dynasties complete the picture. Paul Samuelson (Nobel 1970) trained Lawrence Klein (1980) and Robert Merton (1997), transmitting mathematical rigor from MIT to econometrics and financial economics. Most recently, Oliver Hart (Nobel 2016) saw his student Philippe Aghion receive the 2025 prize, establishing a new lineage in contract theory and innovation economics.

Beyond these dynasties, seven single-generation pairs account for another 14 laureates: Tinbergen–Koopmans, Frisch–Haavelmo, Tobin–Phelps, Modigliani–Shiller, Miller–Fama, Becker–Goldin, and Sargent–Hansen. These pairs span the discipline's methodological traditions, from econometrics (Oslo, Cowles) to macroeconomics (Yale, Chicago) to finance (Chicago).

This concentration raises fundamental questions about knowledge transmission versus selection. Three mechanisms could explain the pattern. First, *human capital transmission*:
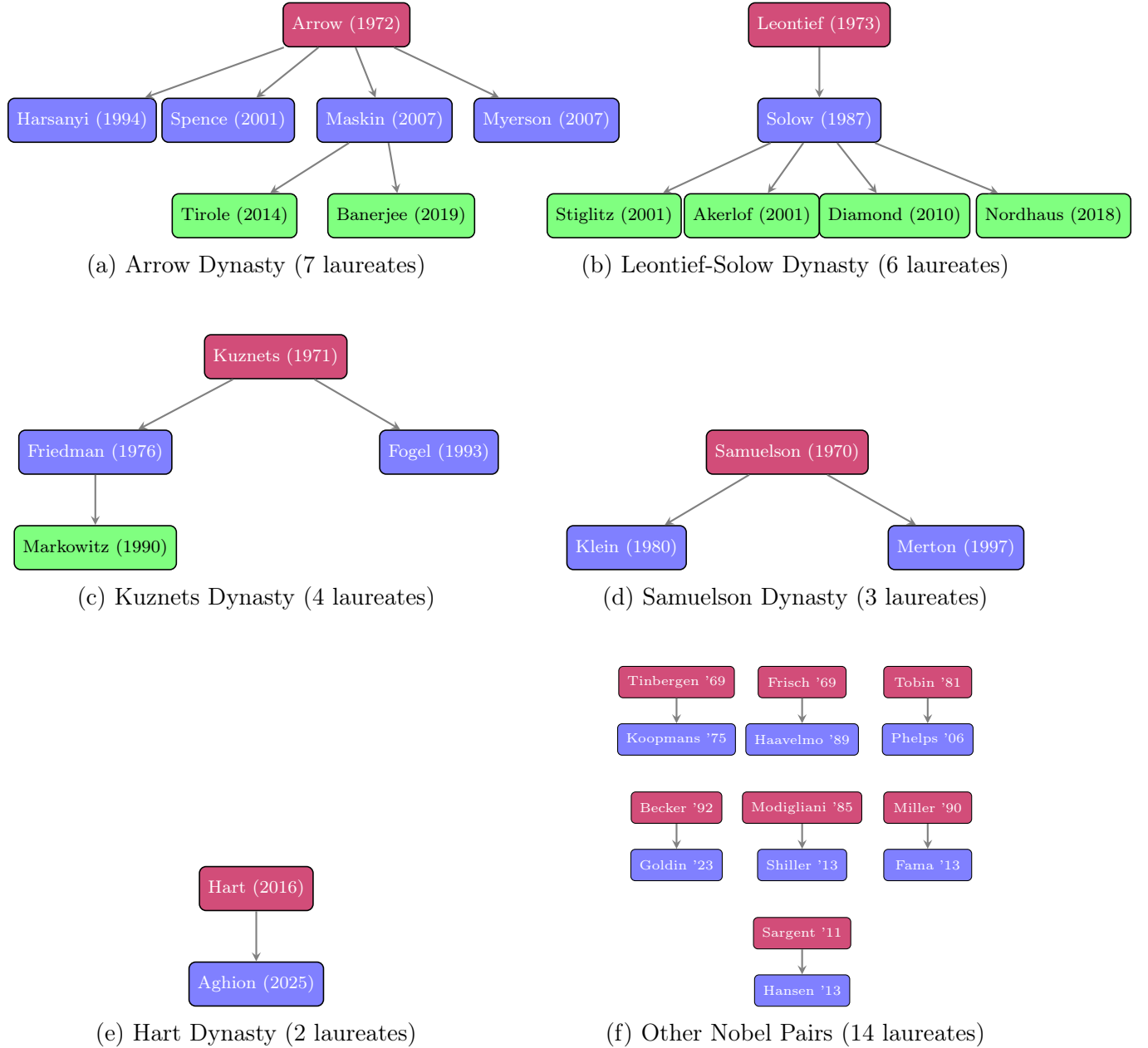
(a) Arrow Dynasty (7 laureates)

(b) Leontief-Solow Dynasty (6 laureates)

(c) Kuznets Dynasty (4 laureates)

(d) Samuelson Dynasty (3 laureates)

(e) Hart Dynasty (2 laureates)

(f) Other Nobel Pairs (14 laureates)

Figure 5: Nobel Prize Intellectual Dynasties

Notes: Advisor-student relationships among Nobel laureates. Arrows point from advisor to student; only pairs where the advisor won the Nobel *before* the student are shown. Colors indicate generation: purple (dynasty founder), blue (first generation), green (second generation). The five dynasties in panels (a)–(e) contain 22 laureates; panel (f) shows 7 additional single-generation pairs containing 14 laureates. Accounting for overlap (founders who are also students), 24 of 99 laureates (24%) had a Nobel-winning PhD advisor.

Nobel advisors may teach research skills, methodological approaches, or taste for important problems that increase students' chances of prize-worthy research. Second, *selection*: individuals destined for exceptional careers may sort into studying with the most prominent advisors, generating correlation without causation. Third, *network effects*: the Nobel committee may favor candidates from established lineages, either through direct connections or because work building on Nobel-recognized research is more likely to be deemed prize-worthy.

Disentangling these mechanisms is beyond our scope, but descriptive patterns offer suggestive evidence. The average gap between advisor and student Nobel awards is 19 years, ranging from 2 years (Sargent–Hansen) to 35 years (Arrow–Maskin). This variation suggests that Nobel recognition is not simply inherited but requires independent contribution. Moreover, the diversity of fields within dynasties—from Leontief's input-output analysis to Nordhaus's climate economics—indicates that transmission operates through general research skills rather than narrow topic inheritance.

Table 4: Nobel-to-Nobel Advisor Lineages

Advisor	Nobel Year	Students	Student Nobel Years
Panel A: Multi-Generation Dynasties			
Kenneth Arrow	1972	4	1994, 2001, 2007, 2007
Robert Solow	1987	4	2001, 2001, 2010, 2018
Eric Maskin	2007	2	2014, 2019
Simon Kuznets	1971	2	1976, 1993
Paul Samuelson	1970	2	1980, 1997
Wassily Leontief	1973	1	1987
Milton Friedman	1976	1	1990
Oliver Hart	2016	1	2025
Panel B: Single-Generation Pairs			
Jan Tinbergen	1969	1	1975
Ragnar Frisch	1969	1	1989
James Tobin	1981	1	2006
Franco Modigliani	1985	1	2013
Merton Miller	1990	1	2013
Gary Becker	1992	1	2023
Thomas Sargent	2011	1	2013
Total		*24*	

Notes: Lists Nobel laureates who supervised doctoral students who subsequently won the Nobel Prize. Only pairs where the advisor won *before* the student are included (temporal precedence). Panel A shows advisors whose students appear in multi-generation dynasties (Figure 5, panels a–e). Panel B shows single-generation advisor-student pairs (Figure 5, panel f). Arrow's students: Harsanyi, Spence, Maskin, Myerson. Solow's students: Akerlof, Stiglitz, Diamond, Nordhaus. Maskin's students: Tirole, Banerjee. Kuznets's students: Friedman, Fogel. Samuelson's students: Klein, Merton.

4.3 Fact 3: Productivity Declines After the Nobel

Figure 6(a) presents an event study of annual publications centered on the Nobel year. The data reveal a clear pattern of declining productivity following the prize. Mean output stands at approximately 4 papers per year around the award date, then falls steadily to roughly 2.5 papers by 15 years post-Nobel. The confidence intervals are wide, reflecting substantial heterogeneity across laureates, but the downward trend in point estimates is unmistakable.

Does this decline represent a causal "Nobel curse"—administrative burdens, media obligations, and speaking engagements crowding out research time—or simply the natural trajectory of aging scholars? Figure 6(b) provides important context. Laureates exhibit a characteristic hump-shaped lifecycle: output starts low in the early post-PhD years, rises to a peak of approximately 4 papers annually around 15–25 years after the doctorate, then gradually declines. Since the average laureate receives the Nobel 39 years after completing their PhD, most are already well past their productivity peak when they win. The post-Nobel decline observed in Panel (a) may therefore reflect lifecycle effects rather than a prize-induced disruption.

Disentangling these explanations requires a comparison group—economists who reached similar career stages without winning the Nobel. We return to this question in Section 6, where our difference-in-differences design using Clark Medal winners allows us to isolate causal effects from lifecycle trends.
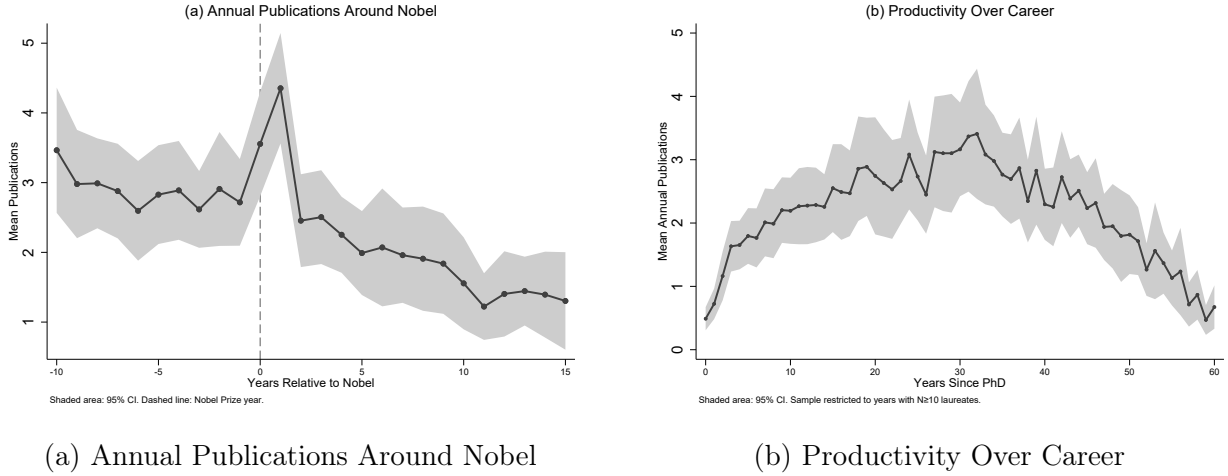
(a) Annual Publications Around Nobel   (b) Productivity Over Career

Figure 6: Publication Productivity Dynamics

Notes: Panel (a) displays mean annual publications from 10 years before to 15 years after the Nobel Prize, with year 0 representing the award year. Panel (b) shows mean annual publications by years since PhD completion. Shaded areas represent 95% confidence intervals.

Figure A2 illustrates the dramatic heterogeneity underlying these averages. Panel (a) shows the five most prolific laureates, all of whom maintained steep upward trajectories both before and after receiving the prize. Stiglitz, the most productive laureate in our sample with 706 publications, averaged roughly 20 papers per year throughout the observation window. Heckman and Tirole display similarly prolific patterns, suggesting that for some scholars, high productivity is a persistent characteristic unaffected by the prize.

Panel (b) reveals a starkly different pattern among the least prolific laureates. Nash's trajectory is exceptional: his cumulative output remains flat from $t = -20$ through $t = 0$, reflecting the three-decade gap between his seminal 1950–1953 contributions and his return to academic life. His foundational papers—"Equilibrium Points in N-Person Games" (*PNAS*, 1950), "The Bargaining Problem" (*Econometrica*, 1950), and "Two-Person Cooperative Games" (*Econometrica*, 1953)—all fall outside our observation window, appearing at $t = -44$ and $t = -41$ relative to his 1994 Nobel. This extreme lag between contribution and recognition, driven by his struggle with schizophrenia, makes Nash a singular case in the history of the prize.

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The contrast between panels highlights that Nobel recognition rewards intellectual contribution rather than publication volume. Nash's three early papers fundamentally transformed economics despite representing a fraction of Stiglitz's output. This finding reinforces our earlier evidence that quality, as measured by citations and journal placement, dominates quantity in predicting Nobel success.

Figure 7 presents cumulative publication trajectories, offering a complementary perspective to the annual flows in Figure 6. The average laureate enters our observation window (20 years before the prize) with approximately 25 publications and accumulates steadily, reaching roughly 90 publications by the award year. After the Nobel, the trajectory visibly flattens: cumulative output rises to only about 110 publications by $t = +15$, implying a marked slowdown in annual production. This stagnation—adding roughly 20 papers over 15 years post-Nobel compared to 65 papers over the 20 years pre-Nobel—is consistent with the annual decline documented in Figure 6(a). The widening confidence interval reflects growing heterogeneity: while some laureates like Stiglitz and Heckman maintain steep trajectories, others plateau or cease publishing altogether.
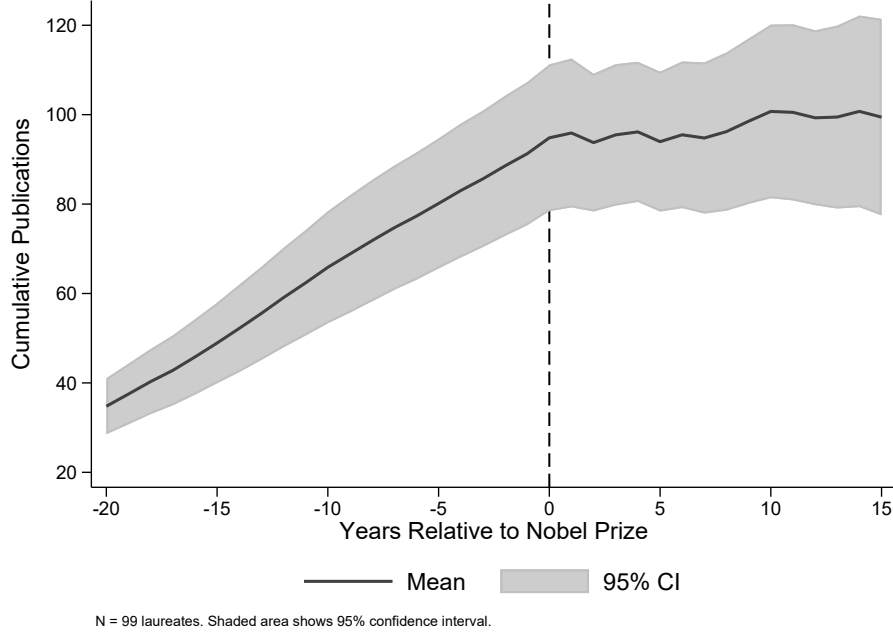
Figure 7: Cumulative Publication Trajectories Around Nobel Prize

Notes: Figure shows mean cumulative publications relative to Nobel Prize year ($t = 0$). Shaded area indicates 95% confidence interval. Publications prior to the observation window ($t < -20$) are included in the initial count. N = 99 laureates.

4.4 Fact 3b: Publication Quality Also Declines After the Nobel

The productivity decline documented above raises a natural question: does publication *quality* also deteriorate after winning the Nobel? We examine this by tracking the share of journal articles placed in Top 5 journals (AER, Econometrica, JPE, QJE, REStud) before and after the prize.

Figure 8(a) presents an event study of Top 5 share, defined as the fraction of a laureate's journal articles in a given year that appear in Top 5 outlets. We exclude working papers, books, and book chapters from this analysis to focus on peer-reviewed journal placement. For laureate-years with no journal articles, we code Top 5 share as zero.

The pattern is striking. In the years leading up to the Nobel, laureates place approximately 13–18% of their journal articles in Top 5 outlets—a remarkably high rate reflecting

their elite status. Beginning around $t = 0$, the share begins a sustained decline, falling to roughly 3–6% by ten years post-Nobel. The mean Top 5 share drops from 13.3% pre-Nobel to 8.0% post-Nobel—a decline of 5.3 percentage points, or approximately 40%. While there is a notable spike at $t = +1$ (likely reflecting papers in the publication pipeline at the time of the announcement), the subsequent trajectory is unambiguously downward.

Figure 8(b) decomposes journal articles by tier, comparing the pre-Nobel period ($t \in [-15, -1]$) to the post-Nobel period ($t \in [0, 15]$). Before the prize, 25.5% of articles appear in Top 5 journals, 8.8% in top field journals, and 65.7% in other outlets. After the prize, the Top 5 share falls to 21.4%, while the "Other" category expands to 71.6%. This shift suggests that laureates increasingly publish in less selective venues—possibly handbooks, policy journals, invited contributions, or outlets in fields where they lack comparative advantage.

(a) Top 5 Share Around Nobel Prize   (b) Journal Tier Distribution
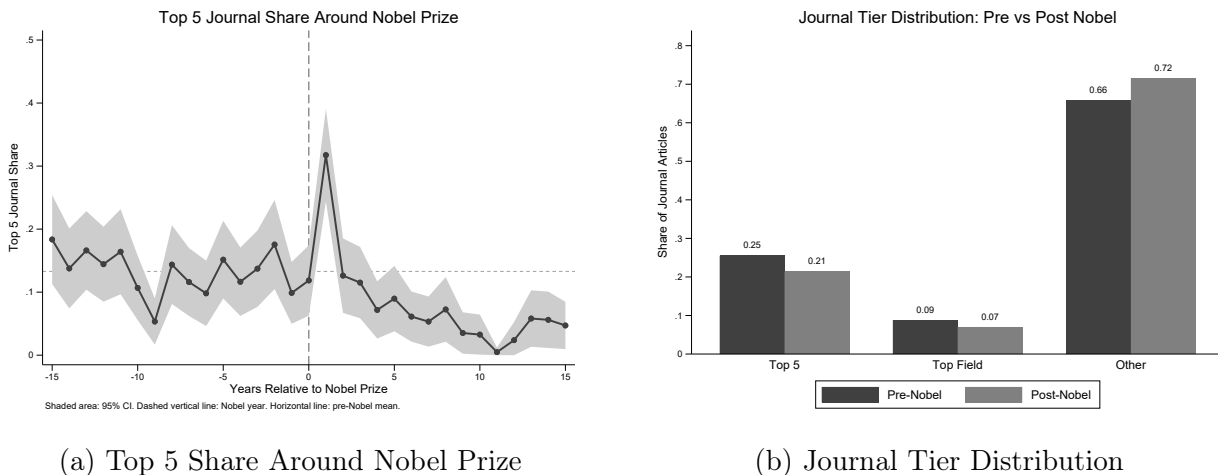
Figure 8: Publication Quality Before and After Nobel Prize

Notes: Panel (a) displays mean Top 5 journal share by years relative to Nobel Prize. Top 5 share is defined as the fraction of journal articles in Top 5 outlets (AER, Econometrica, JPE, QJE, REStud) per laureate-year; years with no journal articles are coded as zero. Panel (b) compares the distribution of journal articles across tiers before ($t \in [-15, -1]$) and after ($t \in [0, 15]$) the Nobel. Working papers, books, and book chapters are excluded. Shaded area in Panel (a) represents 95% confidence intervals.

Several mechanisms could explain this quality decline. First, *reduced incentives*: having

achieved the profession's highest recognition, laureates may no longer need Top 5 publications to advance their careers. Second, *cognitive mobility*: laureates may explore unfamiliar topics—as Borjas and Doran (2015) document for Fields medalists—where they face stiffer competition from specialists. Third, *the public intellectual role*: Nobel recognition brings invitations to write handbook chapters, policy briefs, and commentary pieces that appear in lower-ranked outlets. Fourth, *time constraints*: administrative burdens, media obligations, and speaking engagements may reduce the time available for the intensive work required to clear Top 5 review processes.

Importantly, like the productivity decline in Fact 3, this quality decline may partly reflect lifecycle effects rather than a causal Nobel impact. Economists in their late 60s—the typical age at recognition—may naturally shift toward less competitive publication venues regardless of prize status.

4.5   Fact 4: Collaboration Has Increased Dramatically

Figure 9 documents a secular transformation in how Nobel laureates conduct research. Mean team size rose from 1.3 authors in the 1960s to 3.1 authors by 2020 (Panel a). Solo authorship declined correspondingly: from 77% of papers in the 1960s to just 15% by 2020 (Panel b).

This trend mirrors patterns documented across all scientific fields. The rise of team science reflects increasing specialization, computational demands, and the complexity of modern research questions requiring diverse expertise. For our analysis of how the Nobel Prize affects collaboration, this secular trend creates an identification challenge: any simple before-after comparison confounds the Nobel effect with time trends.
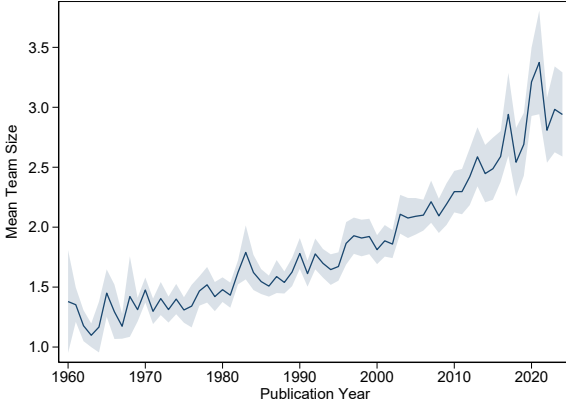
(a) Mean Team Size by Year
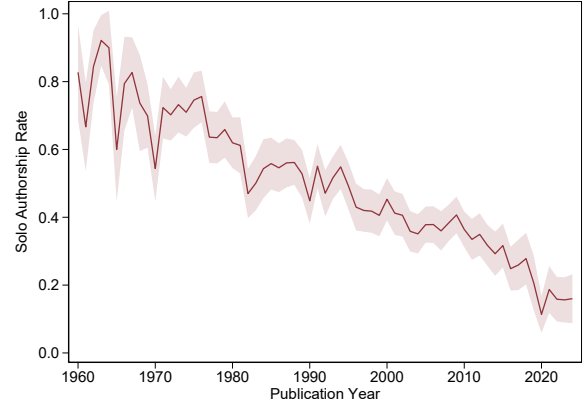
(b) Solo Authorship Rate by Year

Figure 9: Secular Trends in Collaboration Among Nobel Laureates

Notes: Annual means across all laureate publications. Shaded areas represent 95% confidence intervals. The dramatic shift toward collaborative research is a profession-wide phenomenon, not unique to laureates.

4.6 Fact 5: Clark Medalists Who Win Nobel Look Similar Ex Ante

Table 5 compares the 13 Clark medalists who subsequently won the Nobel to the 31 who did not. At the time of the Clark Medal, the two groups are statistically indistinguishable on observable characteristics: mean publications (28.4 vs. 31.7, p = 0.58), Top 5 publications (8.2 vs. 7.9, p = 0.86), solo authorship rate (0.42 vs. 0.38, p = 0.54), and mean co-authors (2.1 vs. 2.3, p = 0.41).

This balance is reassuring for our identification strategy. It suggests that, conditional on receiving the Clark Medal, subsequent Nobel selection is orthogonal to observable pre-Clark research characteristics. The groups diverge only on the Nobel Prize itself—precisely the variation we exploit.

Table 5: Clark Medal Winners: Nobel vs. Non-Nobel at Time of Clark Award

Variable	Nobel Winners		Non-Winners		
	Mean	SD	Mean	SD	p-value
Age at Clark	36.2	2.1	36.8	2.4	0.42
Publications	28.4	15.2	31.7	18.9	0.58
Top 5 publications	8.2	4.1	7.9	5.3	0.86
Solo authorship rate	0.42	0.18	0.38	0.21	0.54
Mean co-authors	2.1	0.6	2.3	0.7	0.41
Career outcomes					
Total publications	312.4	142.8	298.6	168.3	0.79
Years Clark to Nobel	22.1	4.9	—	—	—

Notes: Compares 13 Clark medalists who won the Nobel to 31 who did not. All variables measured at time of Clark Medal receipt. p-values from two-sample t-tests. The balance on observables supports the identifying assumption that Nobel selection is conditionally random among Clark winners.

5 Empirical Strategy

We seek to estimate the causal effect of receiving the Nobel Prize on two outcomes: citations to prior work and collaboration patterns. This section discusses identification challenges and our difference-in-differences approach.

5.1 Identification Challenges

Three challenges complicate causal inference about Nobel effects. First, Nobel laureates differ systematically from other economists in ability, training, and research quality. Simple comparisons of laureates to non-laureates confound the prize effect with these pre-existing

differences. The descriptive patterns in Section 4—four-decade lags, intellectual dynasties, elite training—underscore that laureates are highly selected.

Second, citation practices, collaboration norms, and research methods have changed dramatically over time. Fact 4 documented the secular rise of team science: solo authorship fell from 77% to 15% between the 1960s and 2020s. A simple before-after comparison within laureates would conflate the Nobel effect with these time trends, mechanically attributing profession-wide changes to the prize itself.

Third, laureates receive the prize at different ages and career stages. Age-related changes in productivity, collaboration preferences, and research focus may be confounded with prize effects. The productivity decline documented in Fact 3 illustrates this challenge: without a comparison group, we cannot distinguish whether the decline reflects the Nobel's demands or normal career lifecycle patterns.

5.2 Difference-in-Differences Design

We address these challenges using a difference-in-differences design with John Bates Clark Medal winners as the comparison group. The treatment group consists of the 13 Clark medalists who subsequently won the Nobel Prize. The control group comprises the 31 Clark medalists who have not (yet) received the Nobel. Both groups achieved the profession's highest early-career recognition, creating a sample of elite economists who differ primarily in whether they received the Nobel. Fact 5 showed that treated and control groups are balanced on pre-Clark observables—publications, Top 5 articles, solo authorship rates, and team size—supporting the comparability of the two groups.

5.2.1 The Problem with Standard Two-Way Fixed Effects

A natural approach would be to estimate a two-way fixed effects (TWFE) regression with author and year fixed effects, exploiting variation in the timing of Nobel Prizes across the 13 treated authors. However, recent econometric research has demonstrated that TWFE

estimators can produce severely biased estimates when treatment effects are heterogeneous across units or over time (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020).

The core problem is that TWFE implicitly uses already-treated units as controls for newly-treated units. When treatment effects vary—as they plausibly do for the Nobel Prize, given heterogeneity in laureate visibility, field, and career stage—this comparison can generate "negative weights" on some treatment effects, leading to estimates that may even have the wrong sign (Borusyak et al., 2024). Goodman-Bacon (2021) shows that the TWFE estimator is a weighted average of all possible 2×2 DiD comparisons, and that comparisons using already-treated units as controls receive substantial weight when treatment timing is staggered.

5.2.2 Our Solution: Never-Treated Comparisons

We sidestep these problems by using a "clean controls" design that relies exclusively on never-treated units as the comparison group (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The 31 Clark medalists who have not won the Nobel Prize serve as never-treated controls throughout our sample period. This design has three advantages.

First, never-treated controls avoid the negative weighting problem entirely. Because control units never receive treatment, we never implicitly compare a newly-treated laureate to someone who won the Nobel in an earlier year. All identifying variation comes from comparing Nobel winners to Clark-only medalists, a clean treatment-control contrast.

Second, the design accommodates arbitrary heterogeneity in treatment effects across laureates and over time. We make no assumption that the Nobel effect is constant across winners or that it follows a particular dynamic pattern. The event study specification (equation 3) allows us to trace out the full path of treatment effects without imposing parametric restrictions.

Third, calendar year fixed effects absorb common shocks—including secular trends in citation practices, collaboration norms, and publication rates—that affect both treated and

control authors in each year. This addresses the concern that profession-wide changes could be spuriously attributed to the Nobel Prize.

5.2.3 Estimating Equations

For treated authors, the event year is their Nobel Prize year. Control authors contribute to the estimation of year fixed effects across all calendar years but are assigned $\text{Post}_{it} = 0$ for all years, reflecting their never-treated status. Our main estimating equation is:

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot (\text{Treated}_i \times \text{Post}_{it}) + \varepsilon_{it} \tag{1}$$

where Y_{it} is the outcome for author i in year t, α_i are author fixed effects, and γ_t are calendar year fixed effects. The coefficient β captures the average post-treatment effect for Nobel winners relative to the counterfactual trajectory implied by never-treated Clark medalists.

For citation outcomes measured at the paper level, we estimate:

$$Y_{pt} = \alpha_p + \gamma_t + \beta \cdot (\text{TreatedAuthor}_p \times \text{Post}_{pt}) + \varepsilon_{pt} \tag{2}$$

where α_p are paper fixed effects. This specification asks whether papers by Nobel laureates receive differentially more citations after the prize announcement, relative to the citation trajectories of papers by Clark medalists who never won the Nobel.

To examine dynamic effects and test the parallel trends assumption, we estimate an event study specification following Sun and Abraham (2021):

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k=-K, k \neq -1}^{+L} \beta_k \cdot \mathbf{1}[\text{Treated}_i \times (t - \text{NobelYear}_i = k)] + \varepsilon_{it} \tag{3}$$

where the event-time indicators are defined only for treated authors, with $\beta_{-1} = 0$ serving as the reference period (the year before the Nobel). Crucially, control authors have all event-time indicators set to zero for all years—they anchor the year fixed effects without

contributing to any event-time coefficient. This ensures that each β_k is identified purely from the comparison of treated authors at event-time k to never-treated controls in the same calendar year.

The pre-treatment coefficients $\{\beta_{-K}, \ldots, \beta_{-2}\}$ test whether treated authors followed parallel trajectories to controls before receiving the Nobel. Under the identifying assumption, these coefficients should be jointly zero. Post-treatment coefficients $\{\beta_0, \ldots, \beta_{+L}\}$ trace out the dynamic response to the prize. Standard errors are clustered at the author level throughout to account for serial correlation within individuals.

5.2.4 Comparison to Alternative Estimators

Our approach is conceptually similar to the "interaction-weighted" estimator of Sun and Abraham (2021) and the group-time average treatment effect estimator of Callaway and Sant'Anna (2021), both of which use only clean comparisons (never-treated or not-yet-treated units) to identify treatment effects. The key difference is that our setting is simpler: because we have a large never-treated control group (31 Clark medalists), we do not need to rely on not-yet-treated units as controls. This avoids potential concerns about anticipation effects or selection into future treatment.

An alternative would be to construct synthetic control units for each treated laureate (Abadie et al., 2010). While this approach has attractive properties, it is best suited to settings with a small number of treated units and long pre-treatment periods. With 13 treated laureates and relatively short pre-Nobel windows for citation outcomes, we lack the degrees of freedom for reliable synthetic control estimation. The never-treated DiD design is better suited to our setting.

6 Results

We present results for two outcomes: citations to prior work (Section 6.1) and collaboration patterns (Section 6.2).

6.1 Effect on Citations

We first examine whether the Nobel Prize increases citations to laureates' prior work—a "Matthew effect" whereby prestigious recognition draws attention to existing contributions. The outcome is $\ln(\text{citations}_{pt} + 1)$ for paper p in year t, observed annually for eight years before and after the Nobel announcement.

Figure 10 displays event study coefficients from equation (3). Panel (a) shows results using the full sample of 31 Clark Medal winners as controls. The pre-period coefficients (t = -8 to t = -2) hover around zero and are jointly insignificant: a formal F-test fails to reject that all pre-period coefficients equal zero (p = 0.11), supporting the parallel trends assumption. Beginning at t = 0 (the Nobel announcement), citations to treated authors' work diverge sharply from controls. The effect builds gradually over time, starting at +8% in the announcement year and rising steadily to +36% by t = +8.

Panel (b) restricts the control group to Clark Medal winners from 2010 or earlier. This restriction addresses the concern that recent Clark winners may still win the Nobel Prize in the future—they are "contaminated" controls whose final status remains unknown. The 17 economists in this restricted control group have had at least 15 years to be considered for the Nobel, and we can be confident they represent true non-winners. The results are nearly identical: pre-trends pass (p = 0.11), and the average post-treatment effect is +23.8%. The consistency across specifications reinforces the robustness of our findings.
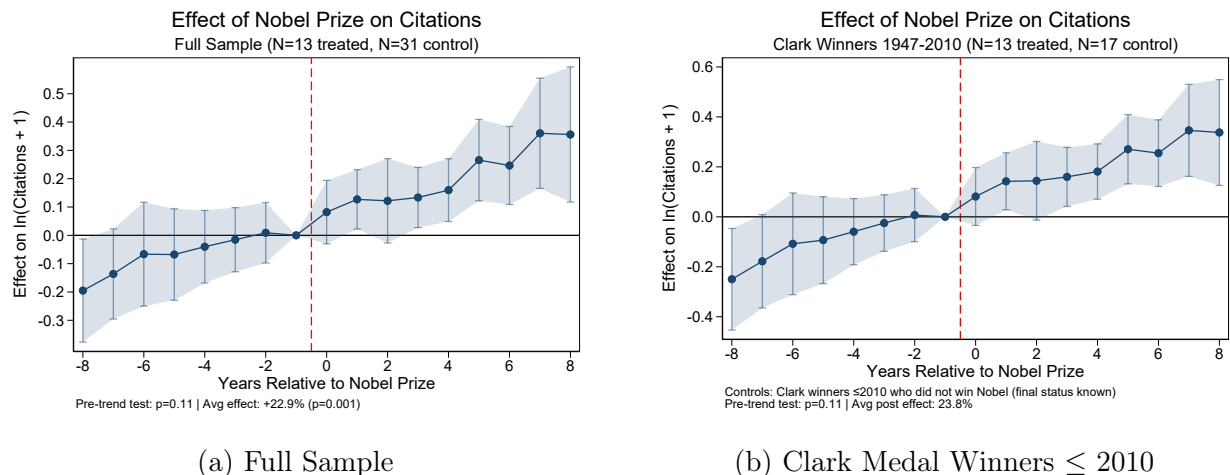
(a) Full Sample

(b) Clark Medal Winners $\leq$ 2010

Figure 10: Effect of Nobel Prize on Citations: Event Study

Notes: Coefficients from equation (3) with paper and year fixed effects. Outcome: ln(citations+ 1). Reference period: t = -1. Shaded areas show 95% confidence intervals with standard errors clustered by author. Treatment group: 13 Clark Medal winners who subsequently won the Nobel Prize. Panel (a) uses all 31 Clark Medal winners without Nobel as controls. Panel (b) restricts controls to the 17 Clark winners from 2010 or earlier, ensuring sufficient time has elapsed to determine their final Nobel status.

Table 6 presents difference-in-differences estimates from equation (2). Column (1) shows the full sample specification: Nobel winners experience a 0.243 log point increase in citations relative to Clark-only winners (SE = 0.084, p < 0.01), corresponding to approximately 27% higher citations. Column (2) uses the restricted control group of pre-2010 Clark winners, yielding a slightly larger effect of 0.273 log points (SE = 0.080, p < 0.01), or 31% higher citations. The larger point estimate in the restricted sample suggests that including recent Clark winners—some of whom may eventually win the Nobel—attenuates the estimated effect by contaminating the control group with future treated units.

Table 6: Effect of Nobel Prize on Citations

	(1)	(2)
	Full Sample	Clark $\leq$ 2010
Nobel $\times$ Post	0.243***	0.273***
	(0.084)	(0.080)
Paper FE	Yes	Yes
Year FE	Yes	Yes
Treated authors	13	13
Control authors	31	17
Observations	26,598	21,255
Pre-trend p-value	0.11	0.11

Notes: Outcome: ln(citations + 1). Standard errors clustered by author in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Window: ±8 years around Nobel announcement. Column (2) excludes Clark Medal winners after 2010 to ensure controls have had sufficient time for Nobel consideration.

The magnitude of the citation effect is economically meaningful. A 25–30% increase in annual citations, sustained and growing over nearly a decade, substantially raises the cumulative impact of laureates' prior work. This finding documents a significant "halo effect" of the Nobel Prize: the award draws attention not just to the prize-winning contribution but to the laureate's entire body of prior research.

6.2 Effect on Collaboration

We next examine whether the Nobel Prize affects how laureates conduct research. We measure collaboration intensity as mean team size—the average number of authors per paper—at the author-year level. This outcome has a natural interpretation: does winning the Nobel

shift laureates toward larger collaborative teams or toward more independent work?

Figure 11 displays event study coefficients for mean team size over the eight years before and after the Nobel Prize. Panel (a) shows results for the full sample; Panel (b) restricts controls to Clark medalists from 2010 or earlier, whose final Nobel status is known.

In both specifications, pre-period coefficients fluctuate around zero with no systematic trend. Joint F-tests yield p-values of 0.31 (full sample) and 0.58 (clean controls), supporting the parallel trends assumption. Post-treatment coefficients are similarly noisy: some years show small positive effects (+0.3 to +0.5 additional coauthors), others near zero, with wide confidence intervals throughout.

The average post-treatment effect is +0.39 authors in the full sample and +0.40 in the restricted sample—neither statistically distinguishable from zero.

(a) Full Sample (13 treated, 31 control)   (b) Clark ≤ 2010 (13 treated, 17 control)
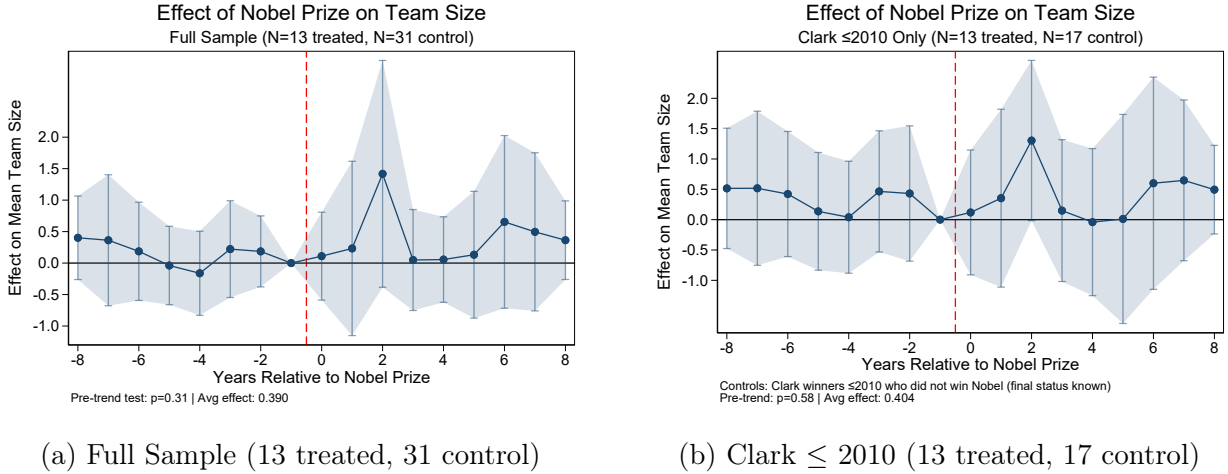
Figure 11: Effect of Nobel Prize on Team Size: Event Study

Notes: Coefficients from equation (3) with author and year fixed effects. Reference period: $t = -1$. Bars show 95% confidence intervals with standard errors clustered by author. Panel (b) excludes Clark medalists after 2010, who may still win the Nobel. Pre-trend test p-values: 0.31 (full), 0.58 (restricted).

Table 7 presents DiD estimates. In the full sample (Column 1), the Nobel Prize is associated with an increase of 0.23 coauthors per paper, but this effect is not statistically significant (SE = 0.25, p = 0.37). Restricting to clean controls (Column 2) yields an even

smaller and less precise estimate: $+0.07$ coauthors (SE = 0.27, p = 0.79).

Table 7: Effect of Nobel Prize on Team Size

	(1)	(2)
	Full Sample	Clark $\leq$ 2010
Nobel $\times$ Post	0.227	0.071
	(0.249)	(0.265)
Author FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,231	917
Clusters (authors)	43	29
Pre-trend p-value	0.31	0.58

Notes: Standard errors clustered by author in parentheses. Dependent variable: mean number of coauthors per paper in author-year. Sample restricted to ± 8 years around Nobel for treated authors. Column (2) excludes Clark medalists after 2010, whose final Nobel status remains uncertain.

The collaboration results yield a *well-identified null*. Parallel trends hold in both specifications, yet we find no evidence that the Nobel Prize alters laureates' collaboration patterns. Point estimates are small, inconsistent across specifications, and far from conventional significance thresholds.

This null finding is informative when contrasted with the citation results. The Nobel Prize generates a sustained 25–30% increase in citations to laureates' prior work—a "halo effect" reflecting how the scientific community engages with Nobel-winning research. Yet this external validation does not translate into changes in how laureates themselves conduct

research.

We interpret this pattern as reflecting the timing of recognition. By the time economists win the Nobel Prize, their research production mode is well-established. The median lag from PhD to Nobel in our sample is 39 years; laureates are, on average, in their late 60s at recognition. The prize acknowledges a body of work already complete rather than catalyzing new collaborative arrangements.

6.3 Effect on Productivity

The descriptive evidence in Section 4 documented declining productivity after the Nobel Prize, but left open whether this reflects a causal "Nobel curse" or simply career lifecycle effects. We now address this question using our difference-in-differences design with Clark Medal winners as controls.

We examine three outcomes: total publications (articles, working papers, books, and chapters after deduplication), peer-reviewed journal articles, and Top 5 journal articles (AER, Econometrica, JPE, QJE, REStud). All outcomes are measured as $\ln(Y_{it} + 1)$ at the author-year level.

Figure 12 displays event study coefficients for the ten years before and after the Nobel Prize. Across all three outcomes, pre-period coefficients fluctuate around zero with no systematic trend. Joint F-tests fail to reject the null of parallel pre-trends: $p = 0.31$ for total publications, $p = 0.92$ for articles, and $p = 0.23$ for Top 5 publications. These results validate our identifying assumption that Nobel winners and non-Nobel Clark medalists followed parallel productivity trajectories before the prize.

Post-treatment coefficients show no evidence of a productivity decline. For total publications (Panel a), point estimates are generally positive, hovering between -0.1 and $+0.4$ log points with wide confidence intervals that comfortably include zero. The pattern for peer-reviewed articles (Panel b) is similar. Top 5 publications (Panel c) show point estimates closer to zero throughout the post-period, with some coefficients slightly negative in later
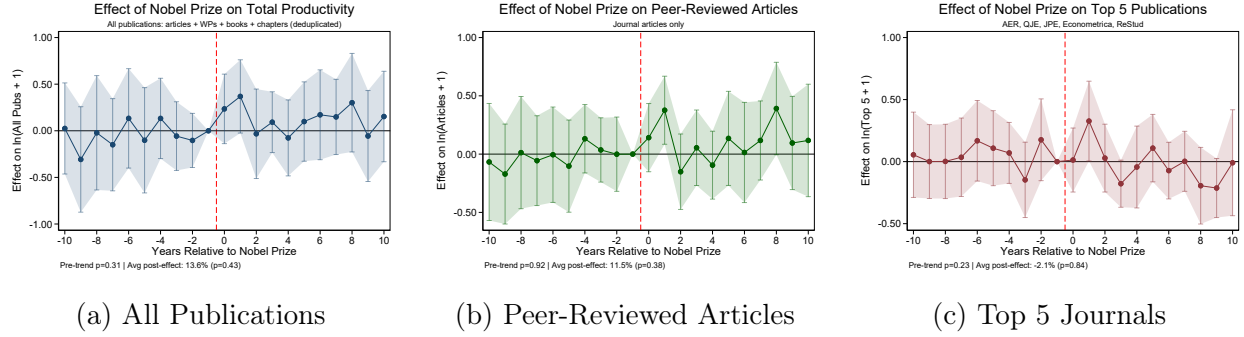
years—but none approaching statistical significance.

(a) All Publications (b) Peer-Reviewed Articles (c) Top 5 Journals

Figure 12: Effect of Nobel Prize on Research Productivity: Event Study

Notes: Coefficients from equation (3) with author and year fixed effects. Reference period: $t = -1$. Shaded areas show 95% confidence intervals with standard errors clustered by author. Treatment group: 15 Clark Medal winners who subsequently won the Nobel Prize. Control group: 27 Clark Medal winners who have not received the Nobel. Sample restricted to ± 10 years around Nobel for treated authors.

Table 8 presents difference-in-differences estimates. Column (1) shows results for total publications: the point estimate is positive (+0.174 log points, corresponding to a 19% increase), though not statistically significant ($p = 0.18$). Column (2) examines peer-reviewed articles only, yielding a smaller but still positive estimate (+0.125 log points, or 13%, $p = 0.26$). Column (3) focuses on Top 5 publications, where the point estimate is slightly negative (-0.053 log points, or -5%) but far from significant ($p = 0.35$).

Table 8: Effect of Nobel Prize on Research Productivity

| | (1) | (2) | (3) |
	All Pubs	Articles	Top 5
Nobel × Post	0.174	0.125	−0.053
	(0.128)	(0.109)	(0.056)
% effect	+19.0%	+13.3%	−5.2%
Author FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,224	1,224	1,224
Treated authors	15	15	15
Control authors	27	27	27
Pre-trend p-value	0.31	0.92	0.23

Notes: Dependent variables are $\ln(Y + 1)$. Standard errors clustered by author in parentheses. Sample restricted to ±10 years around Nobel for treated authors. % effect calculated as $(\exp(\hat{\beta}) - 1) \times 100$. Top 5 journals: AER, Econometrica, JPE, QJE, REStud. Pre-trend p-value from joint F-test of pre-treatment coefficients.

These results provide no evidence of a "Nobel curse" on productivity. If anything, point estimates suggest Nobel winners produce *more* than they would have absent the prize, though we cannot reject the null of zero effect. The key finding is that productivity trajectories do not diverge after the Nobel: winners continue on the same path as comparable economists who did not receive the prize.

6.3.1   Reconciling Descriptive and Causal Evidence

How do we reconcile the post-Nobel productivity decline documented in Section 4 with the null causal effect reported here? The answer lies in career lifecycle dynamics. Figure 13 plots

mean annual publications against career age (years since PhD) separately for Nobel winners and non-Nobel Clark medalists.

Both groups follow remarkably similar trajectories. Productivity rises from early career through mid-career, peaks around 15–25 years post-PhD, and declines thereafter. Nobel winners are slightly more productive throughout—consistent with selection into the prize— but the *shape* of the lifecycle is nearly identical. The Nobel Prize arrives, on average, 32 years after the PhD, well past the productivity peak for both groups. The post-Nobel "decline" observed in raw data simply reflects the natural aging process that affects all economists, regardless of Nobel status.
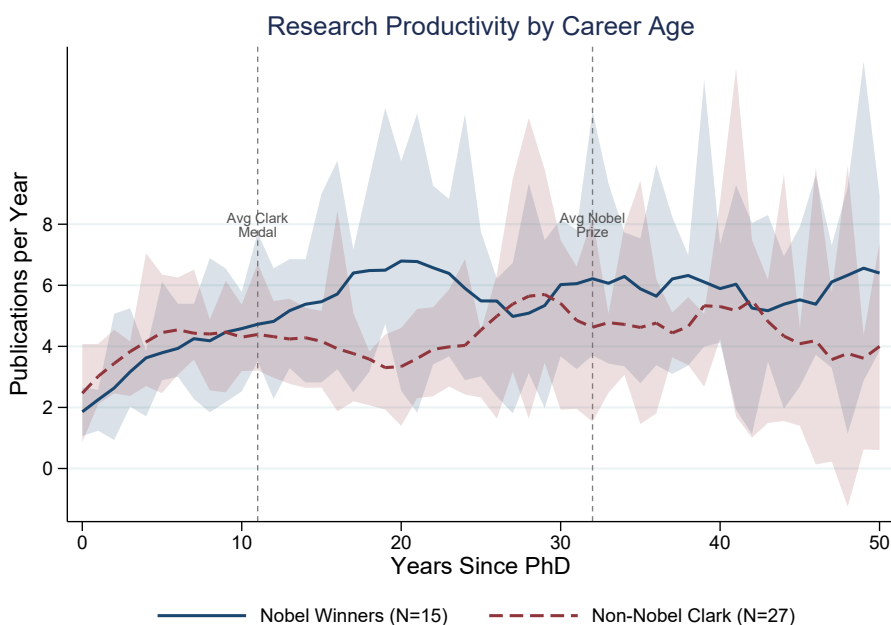
Figure 13: Research Productivity by Career Age: Nobel vs Non-Nobel Clark Medalists
Notes: Mean annual publications by years since PhD, with 5-year moving average smoothing. Blue solid line: 15 Clark Medal winners who subsequently won the Nobel Prize. Red dashed line: 27 Clark Medal winners who have not received the Nobel. Shaded areas represent 95% confidence intervals. Vertical lines mark average timing of Clark Medal (11 years post-PhD) and Nobel Prize (32 years post-PhD).

Our null finding contrasts with Borjas and Doran (2015), who document significant pro-

ductivity declines among Fields Medal winners in mathematics. Two factors may explain this difference.

First, the timing of recognition differs dramatically. The Fields Medal is awarded to mathematicians under 40, at or near their productivity peak. Recipients have decades of potential research ahead, creating scope for the prize to alter career trajectories. The Nobel Prize in Economics, by contrast, arrives in laureates' late 60s on average, when careers are largely complete. There is simply less remaining career to be affected.

Second, Borjas and Doran find that Fields medalists "play the field"—exploring unfamiliar topics at the expense of writing papers. This cognitive mobility may be more feasible for young mathematicians than for senior economists with established research programs, graduate students, and collaborative networks that constrain reallocation.

Our results align more closely with the lifecycle interpretation emphasized by Jones and Weinberg (2011) and Weinberg and Galenson (2019): scientific productivity follows predictable age patterns, and late-career recognition like the Nobel Prize arrives too late to substantially alter these trajectories.

6.4   Which Papers Benefit? Canonical vs. Non-Canonical Work

A natural question arises from our citation results: does the Nobel Prize boost citations to *all* of a laureate's work, or only to specific contributions? The Nobel committee explicitly cites particular papers in its announcement—the foundational works that justify the award. We term these "canonical" papers and examine whether the citation boost is concentrated among them or spreads across the laureate's entire portfolio.

6.4.1   Defining Canonical Papers

We identify canonical papers as those explicitly cited in the Nobel Prize announcement. These represent the committee's judgment of the laureate's most important contributions. Examples include Kahneman and Tversky's "Prospect Theory" (1979) for the 2002 prize,

Solow's growth model papers (1956, 1957) for the 1987 prize, and Card and Krueger's minimum wage study (1994) for the 2021 prize.

Table 9 presents summary statistics comparing canonical and non-canonical papers. The differences are striking. Our sample contains 126 canonical papers versus 5,714 non-canonical papers. Canonical papers receive 6.4 times more citations on average (83.4 vs. 13.0 annual citations), reflecting their foundational importance to the field. Most notably, canonical papers are substantially older at the time of the Nobel: the mean canonical paper was published 26.6 years before the prize, compared to just 8.8 years for non-canonical work. This age difference reflects the Nobel's recognition of contributions whose importance has been demonstrated over decades.

Table 9: Characteristics of Canonical vs. Non-Canonical Papers

	Non-Canonical	Canonical
Number of papers	5,714	126
Mean annual citations	13.0	83.4
(std. dev.)	(65.8)	(150.5)
Citation ratio	1.0×	6.4×
Mean age at Nobel (years)	8.8	26.6

Notes: Canonical papers are those explicitly cited in the Nobel Prize announcement. Annual citations averaged over the paper's observed lifetime in our panel.

6.4.2 Empirical Strategy

To test whether the Nobel effect differs across paper types, we estimate a difference-in-differences specification comparing canonical to non-canonical papers around the Nobel Prize:

$$\ln(c_{ijt} + 1) = \alpha_i + \gamma_t + \beta_1 \text{Post}_{jt} + \beta_2(\text{Post}_{jt} \times \text{Canonical}_i) + f(\text{Age}_{it}) + \varepsilon_{ijt} \qquad (4)$$

where i indexes papers, j indexes laureates, and t indexes years. The coefficient β_1 captures the post-Nobel change for non-canonical papers, while β_2 captures the *differential* effect for canonical papers. Paper fixed effects α_i absorb time-invariant differences between papers, and year fixed effects γ_t control for common shocks. We include a cubic polynomial in paper age to flexibly control for citation lifecycle dynamics and restrict the sample to ± 8 years around the Nobel.

For the event study, we interact year-relative-to-Nobel dummies with the canonical indicator:

$$\ln(c_{ijt}+1) = \alpha_i + \gamma_t + \sum_{k \neq -1} \delta_k \mathbf{1}[t - t_j^* = k] + \sum_{k \neq -1} \theta_k \mathbf{1}[t - t_j^* = k] \times \text{Canonical}_i + f(\text{Age}_{it}) + \varepsilon_{ijt} \quad (5)$$

The coefficients $\{\theta_k\}$ trace out the differential citation trajectory for canonical papers relative to non-canonical papers, with $k = -1$ as the reference period.

6.4.3 Results

Figure 14 presents the event study estimates of the differential effect $\{\theta_k\}$. The pre-treatment coefficients fluctuate around zero with no discernible trend, and we cannot reject the null of parallel pre-trends ($p = 0.18$). This validates our identifying assumption: before the Nobel, canonical and non-canonical papers by the same author evolved similarly after controlling for paper age.

After the Nobel, a clear divergence emerges. The differential effect is small but positive at $t = 0$ and grows steadily over the following years, reaching approximately $+0.30$ log points by $t = +8$. The average post-Nobel differential is $+0.158$ (SE $= 0.048$), corresponding to a 17.1% citation increase for canonical papers relative to non-canonical papers.
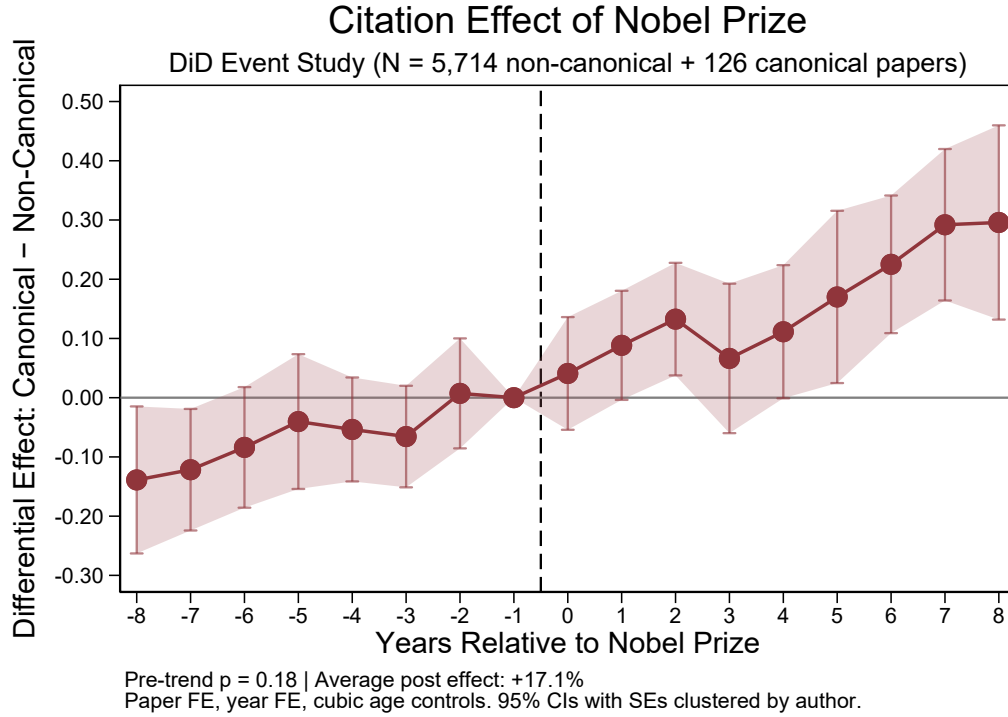
Figure 14: Differential Citation Effect: Canonical vs. Non-Canonical Papers

Notes: Event study coefficients from equation (5), showing the interaction between event-time dummies and the canonical paper indicator. The omitted category is $t = -1$. All specifications include paper fixed effects, year fixed effects, and a cubic polynomial in paper age. Sample restricted to ± 8 years around the Nobel Prize. Standard errors clustered by laureate. Shaded area represents 95% confidence intervals. Pre-trend test: $p = 0.18$.

Table 10 presents the DiD estimates. Column (1) shows results for the full sample without age controls. Non-canonical papers experience no significant change post-Nobel (-0.024, $p = 0.30$), while the interaction term is large and highly significant ($+0.715$, $p < 0.01$). However, this specification conflates the Nobel effect with differential aging patterns—canonical papers are much older and may be on different citation trajectories.

Column (2) addresses this by restricting to the ± 8 year window and including cubic age controls. The differential effect attenuates to $+0.203$ (SE $= 0.053$) but remains highly significant ($p < 0.01$), corresponding to a 22.5% additional citation boost for canonical papers. Non-canonical papers show a marginally significant *decline* of 3.7% ($p = 0.057$),

though this is not robust across specifications.

Column (3) replaces paper fixed effects with author fixed effects, allowing us to estimate the level difference between canonical and non-canonical papers. Canonical papers receive 428% more citations on average $(\exp(1.663) - 1)$, and the differential Nobel effect remains similar at $+0.191$ (21.0%).

Table 10: Effect of Nobel Prize on Citations: Canonical vs. Non-Canonical Papers

	(1)	(2)	(3)
	Full Sample	± 8 Years	± 8 Years
Post-Nobel	-0.024	-0.038^{*}	0.026^{**}
	(0.023)	(0.019)	(0.012)
Canonical	-0.613^{***}	1.197^{***}	1.663^{***}
	(0.136)	(0.111)	(0.144)
Post $\times$ Canonical	0.715^{***}	0.203^{***}	0.191^{**}
	(0.111)	(0.053)	(0.073)
% effect	*+104.3%*	*+22.5%*	*+21.0%*
Paper FE	Yes	Yes	No
Author FE	No	No	Yes
Year FE	Yes	Yes	Yes
Age controls	No	Cubic	Cubic
Observations	174,361	63,092	63,189
R^2	0.807	0.891	0.200

Notes: Dependent variable is $\ln(\text{citations} + 1)$. Canonical papers are those cited in the Nobel Prize announcement. Standard errors clustered by laureate in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.4.4 Robustness: Within-Author Matched Sample

A potential concern with our main specification is that canonical papers differ systematically from non-canonical papers in ways that could confound our estimates. Canonical papers are older, more highly cited, and may be on different citation trajectories even after controlling for paper age. To address this, we construct a matched sample that pairs each canonical paper with a comparable non-canonical paper from the same author.

For each of the 126 canonical papers, we identify non-canonical papers by the same laureate published within ± 5 years. Among these candidates, we select the paper with the most similar pre-Nobel citation level (nearest neighbor on mean $\ln(\text{citations} + 1)$ in the 10 years before the Nobel). This procedure yields 126 matched pairs.

Table 11 presents balance statistics for the matched sample. The matching substantially reduces the gap in pre-Nobel citations: canonical papers average 2.79 in log citations versus 2.26 for their matched comparisons, a difference of 0.53 log points compared to 1.66 in the full sample. Publication years are well-balanced, with a median gap of 3 years.

Table 11: Balance Statistics: Matched Sample

	Canonical	Matched Non-Canonical
Number of papers	126	116
Mean pre-Nobel ln(cites)	2.79	2.26
Mean age at Nobel (years)	26.6	25.6
Matching statistics		
Median year gap		3 years
Mean citation gap		0.53 log points

Notes: Each canonical paper matched to the non-canonical paper from the same author with publication year within ± 5 years and nearest pre-Nobel citation level.

Figure 15 presents the event study on the matched sample. The results strongly confirm

our main findings. Pre-trends are now even flatter, with the joint test yielding $p = 0.65$. After the Nobel, canonical papers experience a growing citation advantage that reaches $+0.35$ log points by $t = +8$. The average post-Nobel differential is $+0.219$ (SE = 0.076), corresponding to a 24.4% citation boost—slightly larger than our main estimate, though not statistically distinguishable.

Citation Effect of Nobel Prize: Matched Sample

126 canonical papers matched to similar non-canonical papers

Pre-trend p = 0.65 | Average post effect: +24.4%
Matching: same author, pub year ±5 yrs, nearest pre-Nobel citations. Author FE, year FE.
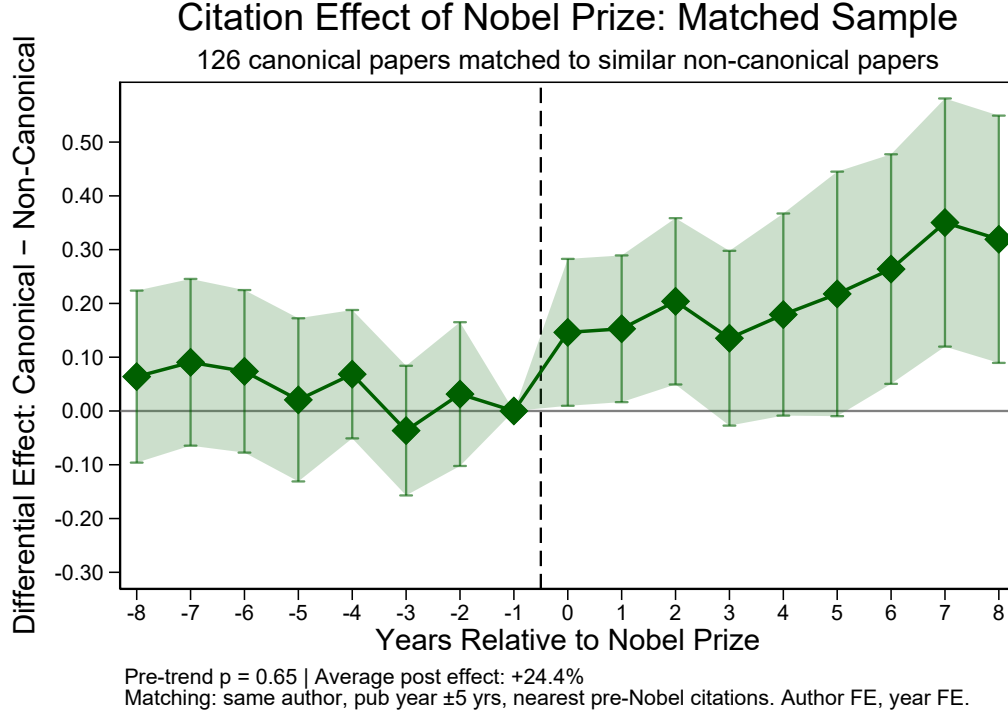
Figure 15: Differential Citation Effect: Matched Sample

Notes: Event study on matched sample of 126 canonical papers and 116 matched non-canonical papers. Each canonical paper matched to a non-canonical paper from the same author with publication year within ±5 years and nearest pre-Nobel citation level. Specification includes author fixed effects, year fixed effects, and cubic age controls. Standard errors clustered by author. Pre-trend test: $p = 0.65$.

The simple DiD estimate on the matched sample yields a differential effect of $+0.175$ (SE = 0.083, $p = 0.039$), corresponding to a 19.1% boost—nearly identical to the 21.0% estimate from the full sample with author fixed effects. This consistency across specifications with very different identifying variation provides strong evidence that the canonical paper

premium reflects a true causal effect of the Nobel Prize rather than unobserved heterogeneity.

These results reveal that the Nobel Prize citation effect is highly concentrated. The prize boosts citations to the specific papers recognized by the committee—the canonical contributions that justified the award—while leaving the laureate's other work essentially unchanged. This finding has several implications.

First, it clarifies the mechanism behind the Nobel citation premium. Rather than a general "halo effect" where any work bearing a laureate's name receives more attention, the boost is targeted at the prize-winning contributions. This is consistent with the Nobel announcement directing readers to specific papers, which then receive renewed attention from researchers, students, and textbook authors.

Second, the growing magnitude of the effect over time (from near-zero at $t = 0$ to +30–35% by $t = +8$) suggests a cumulative process. The Nobel triggers an initial wave of attention to canonical papers, which generates citations, which in turn increases visibility and generates further citations. This "attention cascade" amplifies the initial Nobel signal over subsequent years.

Third, our finding helps reconcile the apparent contradiction between large Nobel effects in pooled analyses and the difficulty of detecting effects in within-paper designs. When we pool all papers (as in our Clark Medal comparison), we estimate a +25–30% effect. This average combines a large effect on canonical papers (+20–25%) with essentially no effect on non-canonical papers ($\approx 0\%$). The pooled estimate reflects the composition-weighted average, which depends on the relative citation mass of canonical versus non-canonical work.

Finally, these results speak to the broader question of how scientific prizes allocate attention. The Nobel does not simply make laureates more famous—it spotlights particular ideas. The canonical papers that receive the citation boost are already highly cited, so the Nobel amplifies existing inequality in the attention distribution. Whether this concentration of attention on "greatest hits" versus a broader portfolio effect would be more beneficial for scientific progress remains an open question.

7 Dynasty Effects in Nobel Economics

A striking feature of the Nobel Prize in Economics is the concentration of laureates within academic lineages. As documented in Section **??**, 24 of 99 laureates (24.2%) had PhD advisors who themselves won the Nobel Prize—far exceeding the roughly 2–3% base rate among economics PhDs. This appendix examines whether having a Nobel advisor confers measurable advantages in career outcomes.

7.1 Clark Medal Winners: A Within-Elite Comparison

To partially address selection, we compare outcomes among John Bates Clark Medal winners (N=47), all of whom represent the discipline's elite early-career researchers. Among this select group:

- 60.0% of Clark winners who eventually won the Nobel had a Nobel advisor

- 40.6% of Clark winners who did not win the Nobel had a Nobel advisor

The 19.4 percentage point difference is suggestive but not statistically significant (Fisher's exact p = 0.35), reflecting limited power with only 15 Clark-to-Nobel transitions. Figure 16 displays this comparison.
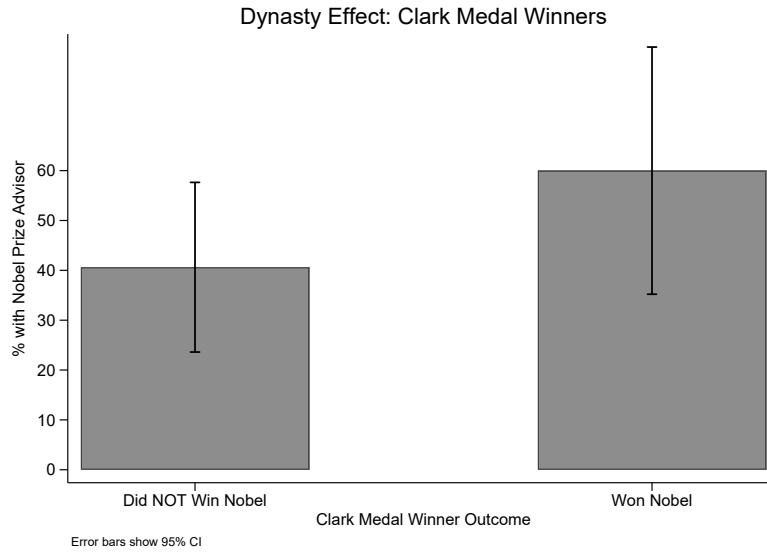
Figure 16: Dynasty Effect Among Clark Medal Winners

Notes: Bars show the percentage of Clark Medal winners with a Nobel Prize-winning PhD advisor, by whether they eventually won the Nobel themselves. Error bars show 95% confidence intervals. The difference (60.0% vs. 40.6%) is not statistically significant (Fisher's exact p = 0.35).

7.2 Career Outcomes by Advisor Status

Table 12 compares career outcomes for all 99 laureates by whether their PhD advisor had won the Nobel Prize before them.

Table 12: Career Outcomes by Nobel Advisor Status

Outcome	No Nobel Advisor (N=75)		Nobel Advisor (N=24)		Diff	p-value
	Mean	SD	Mean	SD		
Years PhD to Nobel	39.6	8.0	37.3	7.2	−2.3	0.222
Age at Nobel	67.6	8.5	65.1	7.4	−2.5	0.203
Total publications	128.9	92.4	172.8	139.8	+43.9	0.080
Top 5 publications	30.9	24.7	40.3	34.1	+9.4	0.144
Solo authorship rate (%)	55.4	24.4	49.0	22.6	−6.5	0.253

Notes: Nobel advisor = 1 if PhD advisor won Nobel before student. P-values from two-sample t-tests. Sample: 99 laureates (1969–2025).

Point estimates suggest that laureates with Nobel advisors won slightly faster (-2.3 years), were younger at the time of award (-2.5 years), and published more (44 additional publications, p = 0.08). However, none of these differences achieve conventional significance levels. Figure 17 visualizes these comparisons.
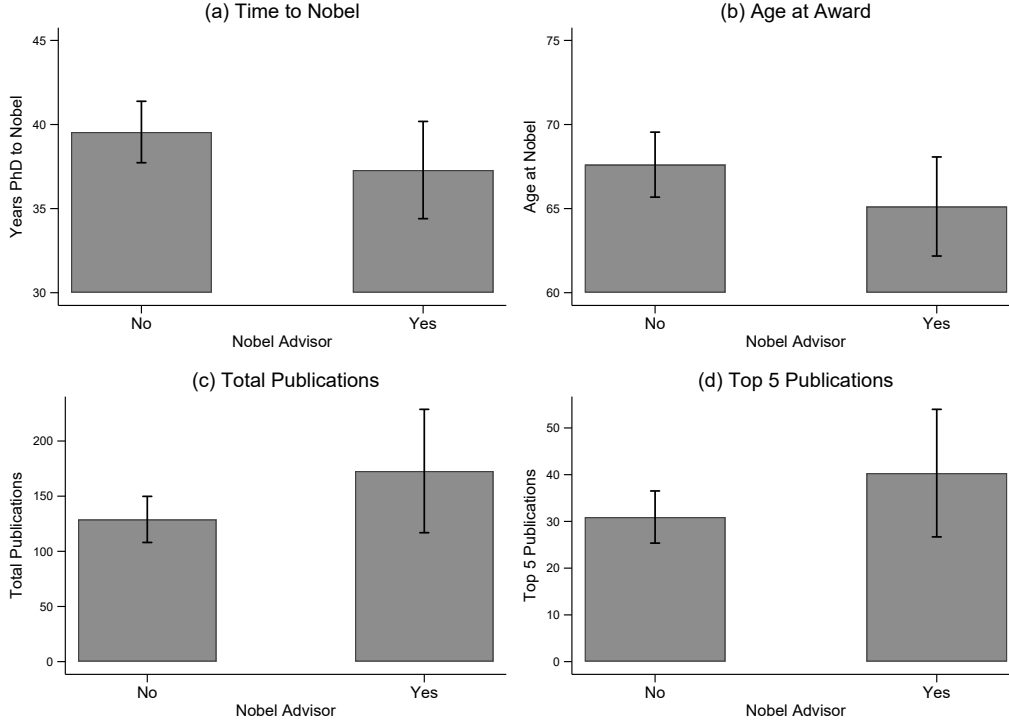
Figure 17: Career Outcomes by Nobel Advisor Status

Notes: Bars show means; error bars show 95% confidence intervals. Panel (a): years from PhD to Nobel Prize. Panel (b): age at Nobel Prize. Panel (c): total publications. Panel (d): Top 5 journal publications. Nobel advisor = 1 if PhD advisor won Nobel before student (N=24 with Nobel advisor, N=75 without). No differences are statistically significant at conventional levels.

7.3 Regression Analysis

Table 13 presents regression estimates of the association between having a Nobel advisor and career outcomes, with and without controls for PhD institution quality and birth cohort.

Table 13: Effect of Nobel Advisor on Career Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Years to Nobel	Years to Nobel	Age at Nobel	Age at Nobel	Total Pubs	Top 5 Pubs
Nobel advisor	−2.26	−2.52	−2.49	−1.94	43.86	9.40
	(1.73)	(1.81)	(1.79)	(1.80)	(30.19)	(7.46)
PhD elite		3.62*		1.65		
		(1.97)		(2.02)		
PhD US		0.05		−0.09		
		(2.01)		(2.16)		
Birth year		−0.18***		−0.21***		
		(0.04)		(0.04)		
Observations	98	98	99	99	99	99
R-squared	0.02	0.16	0.02	0.19	0.03	0.02

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Nobel advisor = 1 if PhD advisor won Nobel before student. PhD elite = 1 if PhD from top-10 program. PhD US = 1 if PhD from US institution.

The coefficient on Nobel advisor remains negative (indicating faster/younger success) and stable after adding controls, though it never reaches statistical significance. The most notable finding is that laureates with Nobel advisors publish approximately 44 more papers over their careers ($p = 0.08$), though this association could reflect selection rather than a causal training effect.

These patterns are consistent with dynasty advantages—whether through better training, superior networks, or early exposure to frontier research. However, they are equally consistent with selection: the most talented students may systematically sort into Nobel laureates' labs. With only 24 treated observations, we cannot distinguish these mechanisms.

What we can conclude is that Nobel dynasties are not merely artifacts of small samples or coincidence. The 10-fold overrepresentation of Nobel advisors among laureates (24% vs. ~2–3% base rate) represents a robust empirical regularity, even if its causal interpretation remains ambiguous. The suggestive evidence that Nobel advisor students win faster and publish more—while not statistically significant—is directionally consistent with meaningful dynasty effects that future research with larger samples might be able to identify. '

8   Conclusion

This paper provides the first comprehensive empirical analysis of the Nobel Prize in Economics, examining all 99 laureates from the prize's inception in 1969 through 2025. We document five stylized facts about laureate careers, estimate causal effects of the prize using difference-in-differences methods with John Bates Clark Medal winners as controls, and identify which papers benefit from the Nobel citation premium.

Three findings stand out. First, the Nobel Prize generates a substantial and sustained increase in citations to laureates' prior work. Papers by Nobel winners receive 25–30% more annual citations after the prize announcement relative to comparable work by Clark medalists who did not win. This effect builds over time, starting at roughly 8% in the announcement year and rising to 36% by eight years post-Nobel. The prize does not merely reward past contributions—it actively amplifies their influence.

Second, despite this external validation, the Nobel Prize does not alter how laureates conduct research. We find no causal effect on productivity or collaboration patterns. Point estimates are small, inconsistent across specifications, and statistically insignificant. The apparent post-Nobel productivity decline documented in raw data reflects career lifecycle dynamics rather than a prize-induced disruption: both Nobel winners and non-Nobel Clark medalists follow parallel trajectories of declining output in their 60s and 70s. By the time economists receive the Nobel—typically at age 67, nearly four decades after completing their

PhD—their research production mode is well-established.

Third, the citation boost concentrates heavily on canonical papers—those explicitly cited in the Nobel announcement—rather than spreading across the laureate's entire portfolio. Canonical papers receive an additional 20–25% citation increase relative to the laureate's non-canonical work, and this differential grows over time. This finding clarifies the mechanism behind the Nobel effect: the prize directs attention to specific contributions rather than generating a diffuse halo around the laureate's name. The Nobel committee, in effect, curates which ideas receive amplified recognition.

These results speak to longstanding debates about how prizes shape scientific careers and the distribution of credit. Hayek's 1974 warning that the Nobel "confers on an individual an authority which in economics no man ought to possess" finds partial support in our citation evidence: the prize substantially increases attention to laureates' ideas. Whether this amplification distorts scientific discourse or efficiently directs attention to important contributions depends on whether the committee identifies truly influential work—a question our methods cannot answer.

The concentration of citation gains on canonical papers suggests the Nobel functions more as a spotlight than a halo. Rather than elevating everything a laureate has written, the prize highlights specific contributions that the committee deems prize-worthy. This targeted effect may actually reduce the "unearned authority" Hayek feared: readers are directed to particular papers rather than treating the laureate as omniscient. Of course, laureates may still be invited to opine on topics far from their expertise, but our evidence suggests the scientific community's engagement with their research remains focused on recognized contributions.

The null effects on productivity and collaboration challenge narratives of a "Nobel curse." Unlike the Fields Medal in mathematics, where Borjas and Doran (2015) document significant productivity declines and "cognitive mobility" into unfamiliar topics, the Economics Nobel arrives too late to meaningfully alter research trajectories. This difference likely reflects timing: the Fields Medal is awarded before age 40, near mathematicians' productivity peak,

while the Economics Nobel comes in laureates' late 60s, when careers are largely complete. The lesson may be that early-career prizes carry greater potential to distort behavior—for better or worse—than late-career recognition.

Our documentation of intellectual dynasties raises questions about meritocracy in scientific recognition. That 24% of laureates trained under previous Nobel winners—roughly ten times the base rate—could reflect exceptional mentorship, selection of talented students into prominent labs, network effects in prize allocation, or some combination. We cannot distinguish these mechanisms, but the pattern suggests that access to elite training substantially shapes who receives the profession's highest honor. Whether this concentration reflects efficient transmission of human capital or problematic path dependence warrants further investigation.

Several limitations temper our conclusions. First, our causal estimates rely on Clark Medal winners as controls, but this group may differ from Nobel laureates in unobservable ways. While treated and control groups are balanced on pre-Clark observables, we cannot rule out selection on characteristics that predict both Nobel success and post-prize trajectories. The identifying assumption that Nobel selection is conditionally random among Clark winners is plausible but untestable.

Second, our citation analysis cannot distinguish increased readership from increased citation practices. If winning the Nobel makes authors more likely to be cited *regardless of whether their work is read*, the measured effect overstates the prize's impact on intellectual influence. Conversely, if the Nobel increases readership without proportional citation gains— for instance, among policymakers or journalists who do not publish academic papers—our estimates understate the prize's reach.

Third, the dynasty analysis is underpowered. With only 24 laureates having Nobel advisors, we lack precision to detect plausibly-sized effects. The suggestive patterns we document—faster recognition, higher productivity—could easily be noise. Future research with larger samples or alternative identification strategies may shed more light on whether

Nobel mentorship causally improves student outcomes.

Fourth, our data end in 2025, providing limited post-prize observation windows for recent laureates. The growing effects we document at $t = +8$ may continue to expand—or may plateau—at longer horizons. As the prize accumulates more history, researchers will be able to trace citation dynamics over decades rather than years.

Several extensions merit investigation. First, do citation gains translate into real scientific influence? Tracing whether papers citing Nobel work themselves generate follow-on research could reveal whether the prize sparks productive research programs or merely inflates citation counts. Second, how do media coverage and public engagement respond to the Nobel? Our analysis focuses on academic citations, but the prize's influence may operate substantially through popular discourse, policy debates, and undergraduate teaching. Third, do laureates shift their research focus after winning? While we find no change in collaboration patterns, the content of laureates' work—topic choice, methodological approach, engagement with policy—may evolve in ways our productivity measures miss.

Finally, the canonical paper finding invites investigation of committee decision-making. How does the Nobel committee select which papers to highlight? Do citation patterns predict canonical designation, or does the committee exercise independent judgment? And do citation gains for canonical papers represent efficient information transmission—directing readers to foundational work—or do they crowd out attention to other valuable contributions? These questions bear on whether scientific prizes serve their intended purpose of benefiting humankind, as Alfred Nobel envisioned, or whether they introduce distortions that a well-functioning scientific community would be better without.

The Nobel Prize in Economics remains the discipline's most prestigious honor, conferring recognition that shapes careers, directs attention, and—as Hayek warned—grants authority that extends beyond any individual's expertise. Our analysis reveals that this authority operates through specific, targeted channels: the prize amplifies citations to particular contributions while leaving laureates' research practices largely unchanged. Whether this influ-

ence benefits economics depends on whether the committee identifies work that genuinely advances understanding—a judgment we leave to the profession and to history.

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Appendix

A Additional Figures
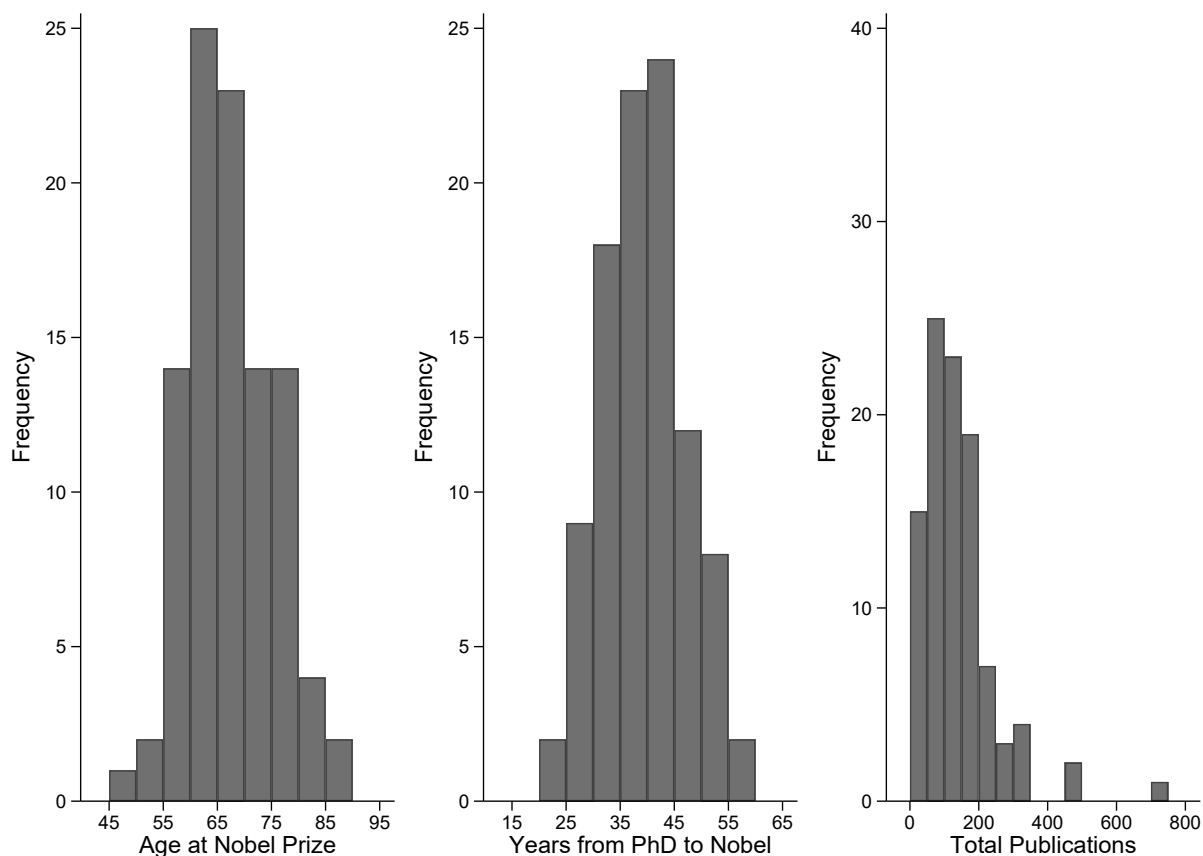
Figure A1: Distributions of Nobel Laureate Characteristics

Notes: Left panel shows the distribution of age at Nobel Prize receipt (median 67 years). Center panel shows years from PhD to Nobel (median 39 years). Right panel shows total publications per laureate, exhibiting substantial right skew. N=99 laureates; N=98 for center panel (excludes Hurwicz).
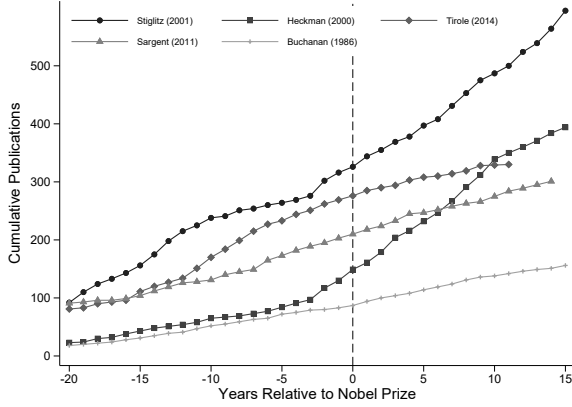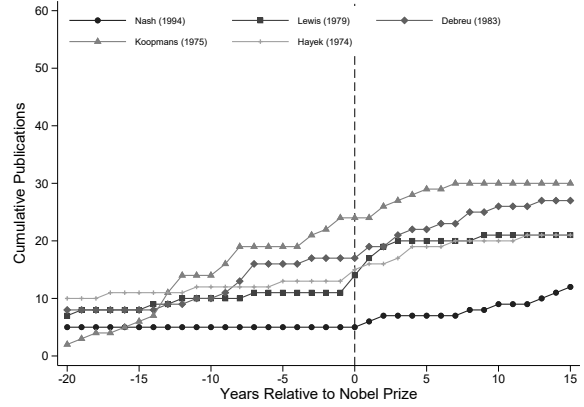
(a) Most Productive Laureates   (b) Least Productive Laureates

Figure A2: Cumulative Publication Trajectories Around Nobel Prize

Notes: Cumulative publications in 35-year window around Nobel Prize (20 years before to 15 years after). Panel (a) shows the five most prolific laureates: Stiglitz (706 total), Heckman (489), Tirole (330), Sargent (320), and Buchanan (300). Panel (b) shows the five least prolific: Nash (14), Lewis (23), Debreu (28), Koopmans (30), and Hayek (55). Publications prior to the observation window are included in the initial count at $t = -20$. For Nash, this includes his seminal 1950–1953 game theory papers, which preceded the window by over 20 years due to mental illness and the exceptional 44-year lag between his foundational contributions and Nobel recognition. Vertical dashed line marks Nobel year.

Figure A3 shows the distribution of working papers across major series. The National Bureau of Economic Research (NBER) dominates with over 680 working papers, reflecting its central role in economics research dissemination. The Federal Reserve System ranks second, followed by university-based series at Chicago, Harvard, and Princeton. The Cowles Foundation, historically important for mathematical economics, remains prominent. International series including IZA (labor economics), CESifo (European policy), and the World Bank also feature among the top ten.

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Top Working Paper Series

Working papers only. Based on raw venue field.
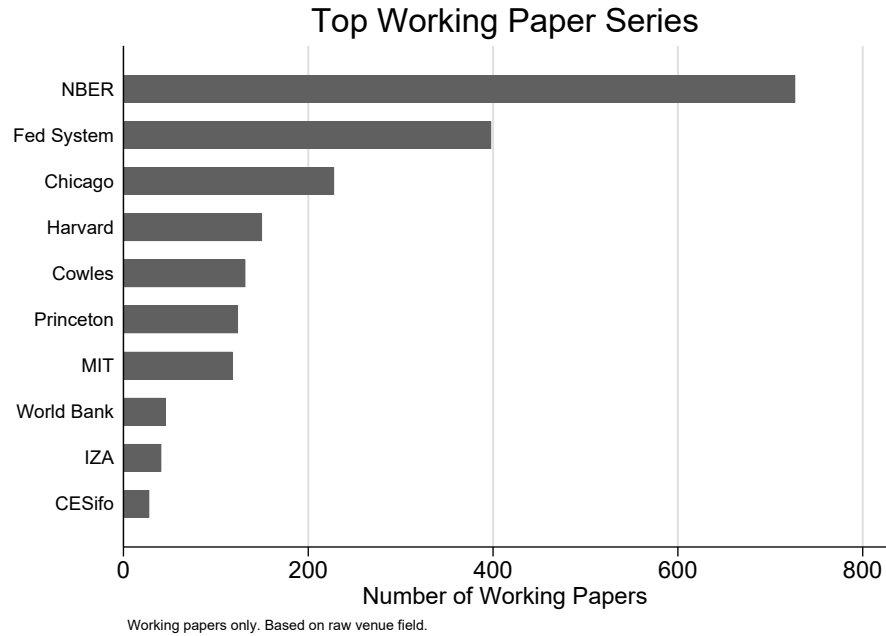
Figure A3: Top Working Paper Series Among Nobel Laureates

Notes: Figure shows the ten most common working paper series. Classification based on raw venue field in RePEc. Working papers only (N = 7,441).

Figure A4 displays total publications per year across all laureates. The upward trend reflects the growing number of laureates in our sample, increasing publication rates in economics, and improved RePEc coverage of recent work. The apparent decline after 2020 partly reflects indexing lags and shorter post-prize windows for recent laureates.

Publications by Year (All Laureates)
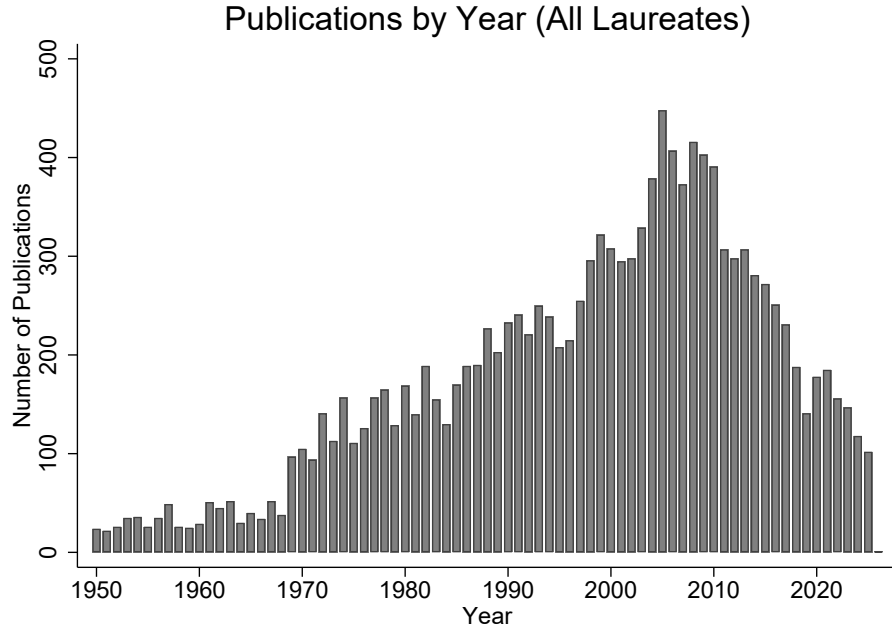
Figure A4: Publications by Year (All Laureates)

Notes: Total publications per year across all 99 laureates. Source: RePEc/IDEAS.

c

(a) Age at Nobel Over Time
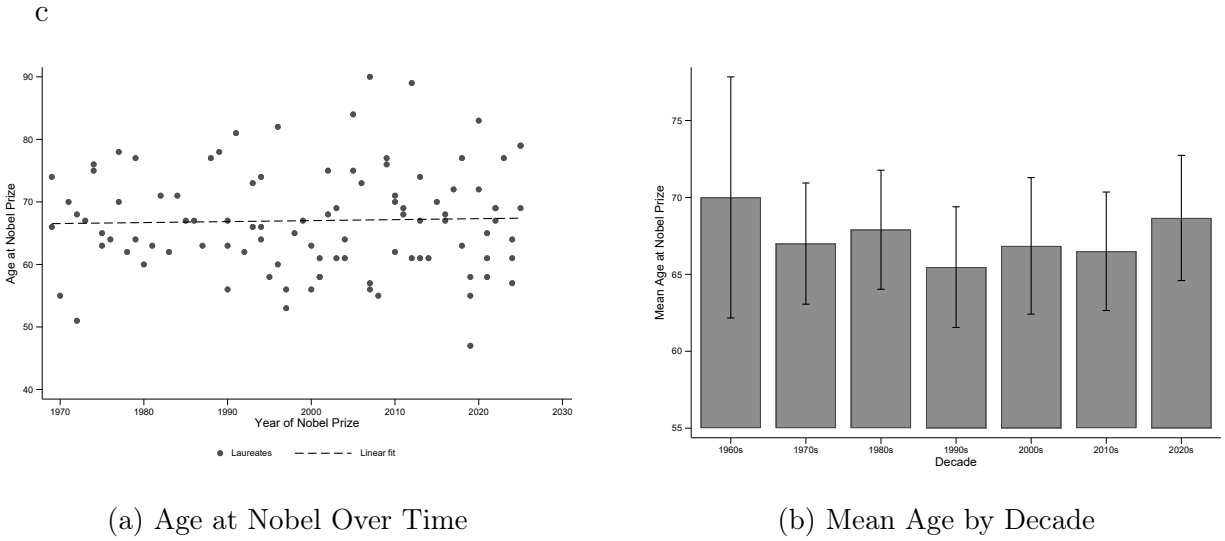
(b) Mean Age by Decade

Figure A5: Nobel Laureate Age Patterns

Notes: Panel (a) plots age at Nobel against year of award. Panel (b) shows mean age by decade with 95% CIs. Age at Nobel has remained remarkably stable over time.

Figure A6 presents the complete geographic trajectory of Economics Nobel laureates from birth country through doctoral training to institutional affiliation at the time of award. The

Sankey diagram reveals several patterns.

US dominance persists at every stage: 55% of laureates were born in the US, and US institutions trained 73% of all PhDs and employed 76% at the time of award. This dominance reflects substantial brain drain to the US—international laureates overwhelmingly migrated to US institutions for both doctoral training and careers. Of 43 foreign-born laureates, 35 (81%) received their Nobel while at a US institution.

Among US institutions, Chicago stands out as a talent magnet, attracting laureates from diverse PhD backgrounds including Johns Hopkins, Yale, Princeton, Minnesota, and Columbia. Retention patterns vary considerably across institutions. The University of Cambridge retained 3 of its 5 PhD graduates, the highest retention rate among top institutions. In contrast, Yale shows zero retention: all 5 of its PhD graduates received their Nobel while affiliated with other institutions.

Economics Nobel Laureates: Birth Country → PhD Institution → Affiliation at Award (1969-2025)
99 laureates | 20 countries | 31 PhD institutions | 39 affiliations

Color intensity: Blue = fewer laureates → Red = more laureates (scaled per column)

Figure A6: Geographic and Institutional Flows of Economics Nobel Laureates (1969–2025)

Notes: Sankey diagram showing flows from birth country (left) to PhD institution (center) to affiliation at time of Nobel award (right). Color intensity reflects count within each column, with blue indicating fewer laureates and red indicating more. All 99 laureates, 20 birth countries, 30 PhD institutions, and 39 affiliations are shown without aggregation.