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Nobel begets Nobel in economics

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ABSTRACT

I construct the professor-student network for laureates of and candidates for the Nobel Prize in Economics. I study the effect of proximity to previous Nobelists on winning the Nobel Prize. Conditional on being Nobel-worthy, students and grandstudents of Nobel laureates are significantly less likely to win. Professors and fellow students of Nobel Prize winners, however, are significantly more likely to win.

1. Introduction

A Nobel Prize begets Nobel Prizes, or so the story goes. There is an extraordinary concentration of winners of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel (Tol, 2022), in departments, as co-authors, as students, and even personally. This may be clusters of quality: The best professors come together in the best schools (Ellison, 2013), inspire, teach and stimulate each other (Azoulay et al., 2010, Borjas & Doran, 2012, Bosquet & Combes, 2017, Oyer, 2006), select the best students (Athey et al., 2007), and train them well Jones and Sloan (2021). But it can also be seen through the lens of nepotism (Combes et al., 2008, Hamermesh & Schmidt, 2003, Laband & Piette, 1994, Medoff, 2003, Carrell et al., 2022, Huber et al., 2022). The Prize Committee solicits nominations from a randomly selected sample of professors of economics[2] *and all living Laureates* (Zuckerman, 1996), who may put their proteges forward. Indeed, Economist Data Team (2021) finds that "[t]he best way to win a Nobel is to get nominated by another laureate". That conclusion relies on archival research, which cannot be done for economics as deliberations remain confidential for 50 years. I instead rely on network theory to explore this question.

The network of professor-student relations for the Nobel laureates in economics (Tol, 2022) has only four graphs: Pissarides has his own family tree, as do Frisch and Haavelmo, and Allais and Debreu. All other Nobelists are related to one another, sometimes distantly, more often closely. Esther Duflo is a good example: All three of her professors won the Nobel Prize, as have two of her

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[1] Many colleagues kindly answered questions about their ancestry. Bengt Kriström, Peter Dolton, Rocco d'Este and three anonymous referees had helpful suggestions and comments.

[2] All professors in the Nordic countries.

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four grand-professors, one great-grand-professor, one great-great-grand-professor, and one great-great-great-grand-professor. Duflo also illustrates that these close familial ties[3] did not stop her from revolutionizing economic methodology.

I here extend the family tree of economic Nobelists to *candidates* for the Nobel Prize. This allows me to test whether well-connected candidates are more likely to win than less-connected ones.

The main contribution of this paper is to show that, conditional on having produced Nobel-worthy research, having a Nobelist as a *student* and *having studied with* a Nobelist significantly and substantially increases the probability of winning the Nobel prize while having a Nobelist as a *professor* reduces the probability of winning.[4] Where Tol (2022) provides evidence for the genealogical clustering of Nobelists, this paper begins to unravel the mechanism underlying such clusters, although it should be noted that I find associations only.

A second contribution is a proposed measure of vertical or cross-distance in a network. In a directed graph, outcloseness measures ancestry and incloseness descent. Crosscloseness measures *shared* ancestry—here, scholars who had the same professor.

A minor contribution is as follows. Statistical inference on a network is difficult because network measures, such as centrality, are descriptive statistics of the population. Changes in a network, on the other hand, can be analyzed statistically using existing methods. The network of Nobelists has changed once a year since 1970. It could have changed in many different ways but it has changed in one particular way. That is, changes in a network can be usefully analyzed using standard choice models.

The paper proceeds as follows. Section 2 discusses the data and methods used. Section 3 presents the results. Section 4 concludes.

2. Data and methods

2.1. Data

The dependent variable in the regressions below is binary, zero for those who could have won the Nobel Prize in economics in year t, one for those who did. The variable of interest is their relationship to Nobelists in years $s \neq t$.

The economics Nobel network documents, for the most part, the relationships between PhD advisers and candidates. However, PhDs are not standardized today and variation was greater in the past. Roy Harrod, for instance, had studied history before being privately mentored in economics by John Maynard Keynes. The network therefore also includes more general mentor-mentee or professor-student relations. Data were taken from AcademicTree, complemented by data from RePEc, Mathematics Genealogy, Wikipedia, curriculum vitae, PhD thesis, and direct inquiries to the people involved. Data are stored on AcademicTree. The network in Tol (2022) ends in 2021, is here updated with Bernanke, Diamnond and Dybvig. Up to 15 generations are included. Christian Haussen, Christian Heyne, August Schlegel and Pierre Varignon are the common ancestors who connect 82 of the 87 Nobelists. These are not household names, indeed not economists. None of the Classical economists we find in textbooks appear in the network, and only two of the renowned neo-Classicists (Menger and Marshall, the latter, ironically, via Keynes). Tol (2022) finds that Karl Knies, who taught John Bates Clark, Eugen Böhn von Bawerk, Richard Ely, and Edwin Seligman, among others, is the central-most professor, followed by Wassily Leontief, the professor of Paul Samuelson, Thomas Schelling, Vernon Smith, Robert Solow, and others. Knies' central role is perhaps surprising. He was a member of the Historical School, arguing that economics should be an empirical science just as it turned to theory.[5] But while the intellectual foundations of economics lie in Great Britain, the roots for training research economists lie in Germany. Young Americans aspiring to be economists saw Knies as the man to help them meet that ambition and they passed the lessons learned to the next generation.

Nobel laureates are readily identified. Nobel candidates are not. There is much speculation about what it takes to win. A necessary condition is to have shaped or created a substantial field of economics; to have opened a new line of inquiry, either thematically or methodologically. This is operationalized by citations in the economics literature, which in recent years typically measure in the tens of thousands, concentrated on a few seminal papers (e.g., Mixon et al., 2017, Chan et al., 2018 note that large number of citations to papers and authors may be partly due to the Matthew Effect (Tol, 2013, Birkmaier & Wohlrabe, 2014)). Clarivate's Citation Laureates meet these criteria and indeed many Citation Laureates later won the Nobel prize—although they missed two of the three Laureates of 2022.

Clarivate's list is arguably incomplete. Cross-checking with the IDEAS/RePEc list of most cited papers, I added Tim Bollerslev. Cross-checking with the IDEAS/RePEc list of highly cited authors, I added Andrei Shleifer, John Campbell and Robert Vishny.[6] These candidates are based on clear criteria that can be applied to data available for recent times.

I added Alvin Hansen, Harold Hotelling, Frank Knight, Abba Lerner, Ludwig von Mises and Oskar Morgenstern, who all died too soon to make it onto any recent lists but would have been worthy. I added Sanford Grossman as a John Bates Clark medalist who saw the co-authors of his most-cited papers win the Nobel prize for something else.[7] Fischer Black would have shared Myron Scholes's Nobel Prize, and Jean-Jacques Laffont Jean Tirole's had they lived long enough. Although David Kreps is a Clarivate Citation Laureate, his co-author Evan Porteus is not. Michael Jensen is a Citation Laureate, but his co-author William Meckling passed too soon for that honor. I further added Guillermo Calvo, Lionel McKenzie, Jacob Mincer, and Henri Theil for their work on

[3] She is also married to a Nobelist.

[4] Totska (2023) predicts the number, age bracket and location of the next winners.

[5] Knies would have delighted in the empirical work of Angrist, Card and Duflo, who are his academic descendants.

[6] I did not use the rankings of Research.com and Google Scholar, because both platforms have issues with citation counts and identification of scholars.

[7] There is an unwritten convention that economists can win only one Nobel prize. John Bardeen won the Nobel Prize in physics twice, Frederick Singer and Barry Sharpless won twice in chemistry, and Marie Skłodowska Curie won physics and chemistry.

sticky prices,[8] general equilibrium, labour, and two-stage least squares, respectively, and Roy Harrod, Kelvin Lancaster, and Mancur Olson for their research on economic growth, the second best, and public goods, respectively. I also added Francine Blau, Ester Boserup, Edith Penrose, and Joan Robinson for their work on inequality, development, firms, and capital, respectively. The full list of candidates and Nobelists is given in Table A.1 in the Appendix. Fig. A.1 shows the number of candidates per year, which starts at 53 in 1970, peaks at 119 in 2004, and falls to 75 in 2022. Fig. A.1 also shows that fraction of winners, which ranges between 0.9% and 4.0%. I conduct a sensitivity analysis on the list of candidates below.

As with the Nobel laureates, I collected information about their ancestry from the Academic Tree. If there was no entry, I checked RePEc Genealogy, Mathematics Genealogy, Wikipedia, CVs, and published theses. If all that failed, I wrote to the candidate or a close associate. I added the information thus collected to the Academic Tree. The data were transferred to Matlab for visualization and analysis. Code and data are available on GitHub.

The final network has 668 nodes and 808 edges. This is too large to meaningfully display in a graph (see Tol, 2022, for an attempt). Figs. A.2–A.5 display subgraphs for the descendants of four Nobel laureates, Leontief, Arrow, Tinbergen and Modigliani. The Leontief graph has four Nobelists in the first generation, eight in the second generation, two in the third generation, and one in the fifth. The graph also shows a number of plausible candidates.

For every Laureate and candidate, I collected year of birth, year of death (if applicable), the year of winning, gender, *alma mater*, and one-digit JEL classifier using Wikipedia as the main source of information.[9] The long list of candidates and Laureates is turned into a short-list of candidates for each year when they (*i*) are alive, (*ii*) are over 40,[10] and (*iii*) have not yet won. This then implies a zero-one variable for people who could have won (0) and people who did (1) for every year from 1970 to 2021. 1969 is excluded because no one had any connection to a previous Nobelist in economics.[11]

The variable of interest is the proximity (defined below) of the candidates in year t to the economics Nobelists of years $s < t$. I distinguish between the proximity to academic ancestors, descendants, and peers. For ancestors and peers, I further distinguish between recent and earlier laureates and, for ancestors, between living and dead professors.

2.2. Methods

The network of professor-student relationships can be represented by a graph, more specifically, a directed acyclic graph or polytree. The distance from a node i in a graph to the rest of this graph can be measured by the Hölder mean

$$D_{i,t}(h) = \left(\frac{1}{N_t} \sum_{j \in Nobel} D_{j,i,t}^{h} \right)^{\frac{1}{h}} \tag{1}$$

where $D_{j,i}$ is the distance from node i to any node j, that is, the number of edges between the i and j. As the interest is in *Nobel* ancestry, attention is restricted to the distance to Nobelists. N_t is therefore the number of previous winners of the Nobel Prize in economics at time t.

It is common to set $h = 1$. The Hölder mean is then the familiar arithmetic mean. However, $D_{i,t}(1) = \infty$ unless scholar i descends from *all* previous Nobelists. There is no such scholar.

For $h = -1$, the Hölder mean is the harmonic mean, which is bounded if some nodes in the network cannot be reached. In other words, the harmonic mean applies to connected as well as unconnected subgraphs: For unreachable nodes $D_{j,i} = \infty$ so $1/D_{j,i} = 0$. Marchiori and Latora (2000) propose this as a measure of distance.

For ease of interpretation, I follow Gil-Mendieta and Schmidt (1996), who propose the *inverse* of the harmonic mean as a measure of closeness $C_{i,t}(p) = D_{i,t}(h)^{-1}$. Scholars who have no economics Nobelists in their ancestry score 0; the score increases with more and more proximate Nobel laureates. This is an *outcloseness* measure. Outcloseness on a polytree measures ancestry. According to this measure, two students of the same Nobelist are both close to their professor, but not to each other (see below).

Recall that I do not use the proximity to all nodes, but only to the Nobel ones. In Equation (1), N is the number of Nobelists and j sums over them. Concretely, therefore, a candidate receives one point for every professor who won the Nobel Prize, half a point for every grandprofessor who did, a third of a point for every Nobel great-grandprofessor, and so on, and zero points for academic ancestors who are not laureates. Note that many economists in the network have more than one Nobel ancestor. The total number of points is then divided by the total number of laureates *at the time*.

The harmonic mean distance emphasizes proximity at the expense of distal relationships: Consider a student with one Nobel professor (distance 1) and one Nobel great-grandprofessor (distance 3). The arithmetic mean distance is 2, the harmonic mean distance is 1.5. That is, the harmonic mean is skewed towards closer relationships.

I also compute an *incloseness* measure, replacing $D_{j,i}$ by $D_{i,j}$ in Equation (1). This measures the distance to Nobel *students*.

Besides outcloseness (ancestry) and incloseness (descent), which are based on the vertical distance *between* generations, I also measure crosscloseness, which is based on the horizontal distances *within* generations. Define the proximity of degree 1 (2) between

[8] And for having a fairy named after him.

[9] Recall that the first Nobel prizes were awarded in 1969, for research done decades before that and published without JEL codes.

[10] Note that this implies that people are considered candidates *before* they appear, e.g., in the Clarivate Hall of Citation Laureates.

[11] Jan Tinbergen was the student and grandstudent of two prominent physicists, Ehrenfest and Boltzmann, who did not win the Nobel prize, however. Tjalling Koopmans, on the other hand, has three Nobel laureates in physics (Bohr, Thomson, Strutt) and one in chemistry (Rutherford) in his ancestry and, of course, one in economics (Tinbergen). Daniel Kahneman is a distant descendant of a medicine laureate (Sherrington).

Table 1
Probability of winning the Nobel Prize.

	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
female	-0.196	0.0263	-0.238	0.0163	-1.633	-0.308	-0.523	0.045
	(-0.27)	(0.10)	(-0.32)	(0.06)	(-1.63)	(-0.79)	(-0.63)	(0.16)
Proximity to Nobel profs	-2.076***	-0.771**	-1.907**	-0.799**	-2.254*	-1.082**	-2.152**	-0.983***
	(-3.43)	(-3.12)	(-3.00)	(-3.01)	(-2.50)	(-2.91)	(-2.95)	(-3.26)
Nobel students	3.642***	1.883***	4.259***	2.201***	6.957***	3.494***	5.049***	2.675***
	(4.15)	(3.83)	(3.32)	(3.44)	(3.51)	(3.47)	(3.36)	(3.70)
Nobel peers	10.93***	5.228***	11.59***	5.522***	16.11***	7.212***	14.22***	6.62***
	(13.85)	(13.83)	(13.46)	(13.65)	(12.54)	(13.21)	(12.58)	(13.11)
Year fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Alma mater fixed effects	No	No	No	No	Yes	Yes	No	No
Field fixed effects	No	No	No	No	No	No	Yes	Yes
Observations	4899	4899	4899	4899	4245	4245	4851	4851

t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

nodes i and j as one minus the number of shared (grand) professors divided by the total number of (grand) professors of i and j. This measure is one for full siblings (double first cousins).[12] The crosscloseness of node i is then the inverse of the harmonic mean horizontal proximity to all other nodes j. See Tol (2023a) for further discussion of distance measures and the required software.

As the number of Nobel laureates grows over time, proximity—outcloseness, incloseness, crosscloseness—to Nobelists is a non-stationary measure. I therefore scale $C_{i,t}$ by $\max_i C_{i,t}$. Absolute proximity is thus replaced by *relative* proximity, where the closest candidate in any year scores one and all others score less than that.

3. Results

Table 1 shows the results of eight regressions. Table A.2 gives the summary statistics for the key variables. The dependent variable is zero-one, so I use logit and probit. I estimate the model with and without year fixed effects, with and without fixed effects for the *alma mater*, and with and without field fixed effects. I treat all previous Nobelists equally (see below). In all eight specifications, the proximity to Nobel students is significant and positive. That is, conditional on being a candidate for the Nobel prize, the probability of winning increases if your students have won before you. This pattern started early: Leontief won after his student Samuelson, Hayek after his student Hicks. It continues today. Wilson won after his students Holmström and Roth (and together with a third student, Milgrom.) Angrist (Card) won after his (grand)student Duflo. One possible explanation is that the surge of interest that accompanies a Nobel Prize leads to a re-appreciation of the foundations on which that work was built.

Proximity to Nobel peers is also positive and significant in all specifications. You are more likely to win if someone from the same PhD programme has won before you. As noted above, three of Wilson's students won the Nobel prize. Arrow, Solow and Samuelson also have three Nobel students, Leontief has four. It is these concentrations of academic siblings and, for Leontief, cousins that explain the significance of the coefficient for peer proximity.

Table 1 shows the estimated coefficients. Fig. 1 shows the effect size, that is, the predicted probability of winning the Nobel prize, using the logit model with year fixed effects, as a function of the relative proximity to Nobel students and peers. The effect size is substantial. In the bottom left corner, those candidates without Nobel students and peers, have a predicted annual win probability of 20% or less. This probability is over 80% for those who are closest to Nobel descendants and siblings.

Proximity to Nobel professors is significant but negative: Students of Nobel laureates are less likely to win. However, there is a strong positive correlation between proximity to Nobel professors and Nobel peers. If the latter is dropped from the regression, the effect of Nobel professors becomes positive but insignificant. Recall, furthermore, that all estimates are conditional on being a candidate. Most candidates have some connection to a previous Laureate. Successful candidates tend to have connections to both Nobel professors and Nobel peers—which is why, conditional on being a candidate and controlling for peers, proximity to Nobel professors reduces the probability of winning the Nobel prize.

The inclusion of fixed effects for the *alma mater* does not change the results in a meaningful way. See Fig. A.6 for the descriptive statistics. Observations are dropped because some universities have candidates but no winners. Cambridge, Chicago, Harvard, LSE, MIT, Oxford, Princeton, Stanford and Yale have significant negative effects for both probit and logit, Carnegie Mellon for logit only. Leiden and Leningrad have positive effects for logit only. Conditional on being a candidate, getting a PhD from a smaller, less prestigious programme increases the probability of winning the Nobel prize.

[12] Proximity of degree n is readily defined but the language becomes tedious. Horizontal proximity based on shared descent can be defined in an analogous way but makes little sense in the current context.

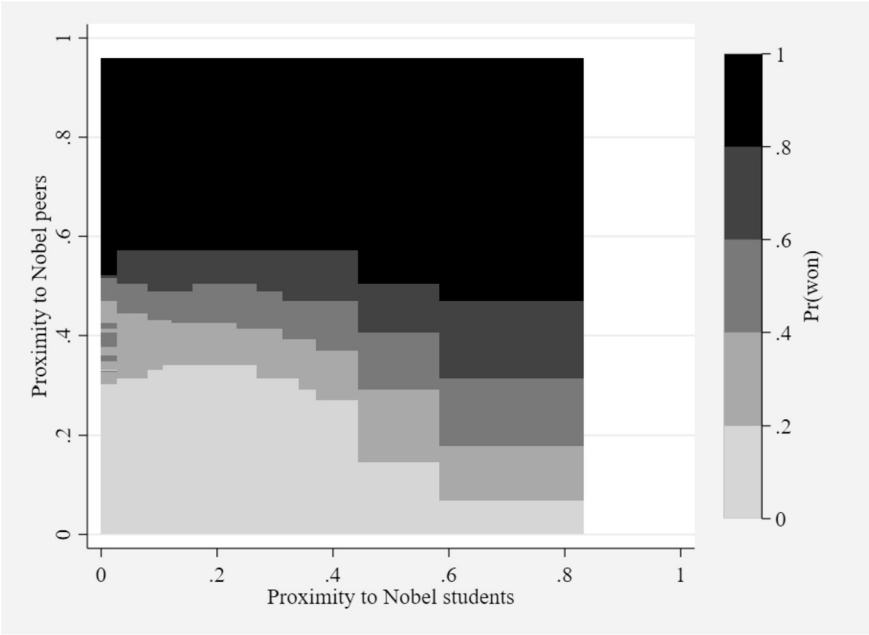

Fig. 1. Probability, conditional on being a candidate, of winning the Nobel prize in economics as a function of the relative proximity to a previously enNobeled student and peer.

Field fixed effects again leave the main results unaffected. See Fig. A.7 for the descriptive statistics. Dummies are significant for JEL-codes D (micro), E (macro), K (law) and Q (environment). Researchers in this field are significantly less likely to win the Nobel Prize, conditional on being a candidate.

Table 1 also includes a gender dummy. Female candidates are less likely to win than male candidates, but this effect is insignificant. Although there are claims to the contrary (but see Liang et al., 2020), women are not discriminated against in this regard—although they may be less likely to be included in the list of candidates.

Table 2 sheds some light on the mechanism. One hypothesis is that Nobel prizes are won on the recommendation of Laureates. Dead people do not write nomination letters, so I split the sample into deceased and living professors. However, no one has won the Nobel Prize after a student or peer has won and died. You can further hypothesize that recent Nobelists more eagerly exercise their powers of patronage. So I split the sample into professors and peers who won within the last 10 years and earlier winners. Professors win within 10 years of their Nobel students.

Table 2 shows that proximity to Nobel professors remains negative when I distinguish between living and deceased professors. The effect size is smaller and insignificant for *deceased* professors. (Don't get any ideas, guys!) It's only weakly significant for living professors. The same result is found when I split proximity to Nobel professors between those who won in the last decade and those who won more than 10 years ago. In the right-most columns, I further split Nobel peers into recent and earlier winners. Earlier laureates have no significant impact, but recent ones do—the effect size increases. In this specification, recently enNobeled professors also have a highly significant, negative effect.

These results suggest that nominations by previous Nobelists play a role. To strengthen the argument, I collected the citation histories of all Nobelists from the Web of Science. I regressed the annual citation number on a linear time trend, and a dummy for the years after an academic relative won the Nobel Prize. See Bjork et al. (2014), Chan et al. (2014), Sangwal (2015), Zhang et al. (2019), Frey and Gullo (2020), Kosmulski (2020) for more advanced analysis. The t-statistics for these dummies are shown in Figs. A.8, A.9 and A.10. The awarding of the Nobel Prize to a professor had a statistically significant impact on citations to his students in 13 cases (who later went on to win anyway), a positive effect in 3 cases, and no significant effect in 7. See Fig. A.8.

The Nobel Prize going to a student positively (negatively) affected the citations of their professors in two cases (one case), and had no statistically significant effects in 5 cases. See Fig. A.9. The Nobel Prize positively (negatively) affects the citation record of fellow students in 6 (12) cases, and not at all in 14 cases. See Fig. A.10. Putting all these results together, previous Nobel laureates do not affect their relatives' chances of winning because they draw more citations to their work.

Table 3 restricts the number of candidates, first by excluding the candidates identified by me and denoted as "ad hoc" in Table A.1, and then by excluding those as well as the candidates found at IDEAS/RePEc. With fewer candidates, the average probability of winning goes up. It does not materially affect the results. Coefficients and significance are almost the same in the limited samples as in the full sample.

As a further robustness check, I reformulate the base specification as a *duration* model, using the exact-partial variant of Cox' proportional hazard estimator (Cox, 1972, Cleves et al., 2016). This is a different conceptualization. Above, I model the *probability* of winning the Nobel Prize in economics. Here, I model both the chance of winning and the *time it takes* to turn that possibility

Table 2
Probability of winning the Nobel Prize.

	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
female	-0.238	0.0163	-0.221	0.0212	-0.221	0.0212	0.182	0.154
	(-0.32)	(0.06)	(-0.30)	(0.08)	(-0.30)	(0.08)	(0.24)	(0.55)
Proximity to								
Nobel students	4.259***	2.201***	4.218***	2.179***	4.218***	2.179***	4.990***	2.153***
	(3.32)	(3.44)	(3.31)	(3.42)	(3.31)	(3.42)	(3.13)	(3.26)
Nobel peers	11.59***	5.522***	11.43***	5.448***	11.43***	5.448***		
	(13.46)	(13.65)	(13.40)	(13.64)	(13.40)	(13.64)		
earlier enNobeled peers							-0.116	0.341
							(-0.08)	(0.50)
recently enNobeled peers							18.28***	8.869***
							(7.96)	(8.16)
Nobel profs	-1.907**	-0.799**						
	(-3.00)	(-3.01)						
deceased Nobel profs			-0.911	-0.413				
			(-1.18)	(-1.35)				
living Nobel profs			-1.428*	-0.582*				
			(-2.49)	(-2.43)				
earlier enNobeled profs					-0.911	-0.413	-1.208	-0.450
					(-1.18)	(-1.35)	(-1.31)	(-1.28)
recently enNobeled profs					-1.428*	-0.582*	-2.024***	-0.892***
					(-2.49)	(-2.43)	(-3.10)	(-3.15)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alma mater fixed effects	No	No	No	No	No	No	No	No
Field fixed effects	No	No	No	No	No	No	No	No
Observations	4899	4899	4899	4899	4899	4899	4899	4899

t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3
Probability of winning the Nobel Prize.

	all		without *ad hoc*		without IDEAS/RePEc	
	Logit	Probit	Logit	Probit	Logit	Probit
female	-0.238	0.0163	0.306	0.218	0.296	0.213
	(-0.32)	(0.06)	(0.42)	(0.79)	(0.40)	(0.77)
Proximity to						
Nobel profs	-1.907**	-0.799**	-1.992**	-0.860**	-1.965**	-0.848**
	(-3.00)	(-3.01)	(-3.14)	(-3.21)	(-3.10)	(-3.16)
Nobel students	4.259***	2.201***	4.091**	2.136***	4.076**	2.128**
	(3.32)	(3.44)	(3.16)	(3.29)	(3.15)	(3.28)
Nobel peers	11.59***	5.522***	11.50***	5.529***	11.45***	5.505***
	(13.46)	(13.65)	(13.31)	(13.48)	(13.21)	(13.38)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Alma mater fixed effects	No	No	No	No	No	No
Field fixed effects	No	No	No	No	No	No
Observations	4899	4899	4432	4432	4340	4340

t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

into reality. The female dummy is still insignificant. Outcloseness, proximity to Nobel professors, is insignificant too. Incloseness, proximity to Nobel students, is significant and negative: -1.88 with a standard error of 0.64 and a p-value of 0.3%. This implies a hazard ratio of 15%. For every cycle of nomination and award, the chance of winning is 15% lower than it otherwise would have been for candidates who are close to Nobel students. This appears to contrast with the results above. The reason is that, while having a Nobel student increases the chance of winning, this may actually take a while.

Crosscloseness, proximity of Nobel peers, is significant and positive: 8.41 with a standard error of 0.82. As above, having a fellow student win the Nobel Prize increases the chance of winning, and it does so quickly.

I did not include more control variables. Including a quality indicator, such as the number or concentration of citations, would just confirm that all candidates are Nobel-worthy—the Nobel prize is not handed out mechanically. Designing a quality indicator that is robust over five decades and across subdisciplines is not easy and not attempted here. Fig. A.11 shows the total number of citations at the time the Nobel Prize was awarded. There is a general upward trend as the discipline has grown. There is wide variation around that trend. Arthur Lewis had one citation—he wrote books, which are not counted in the *Web of Science*, while Eugene Fama had 34,778—the words "at last" were probably the most common in response to the 2013 announcement.

Some commentators discern a pattern through which different parts of the profession get awarded on the basis of a pre-determined rota. There is undoubtedly some of that going on. Last year's runner-up would be this year's favourite. Subfields or schools that feel overlooked may be more eager to submit nominations.[13] Pigeon-holing candidates is subjective and difficult, particularly since Nobelists tend to win for having broken the mold. Discerning the preferences of the members of selection committee is harder still, let alone the dynamics of the discussions within the committee, the composition of which changes over time. Documenting the sympathies and antipathies that increase and decrease the chance of winning is almost impossible.[14]

4. Discussion and conclusion

I test whether academic relations of previous laureates are more likely to win the Nobel memorial prize in economics. Conditional on being a candidate, the *professors* and *peers* of Nobelists are more likely to win but their *students* are less likely to win. The positive impact of peers is limited to fellow students who won the Nobel prize less than 11 years ago. The negative impact of professors only holds for those who won less than 11 years ago or are still alive. There is no consistent impact of winning the Nobel prize on the citations to the papers of Laureates' students, peers, or professors. Nobelists lobbying for their professors and peers can therefore not be excluded. Your best bet to win a Nobel prize is to make sure your (fellow) students win one first.

There are three big gaps in this research. A study of the archives of the Nobel committee would shed more light on nominations, discussions, and group dynamics. Unfortunately, most of these archives are sealed. It will take a few more decades before a sufficiently large sample is available for study—at least for economics. For the other four Nobel prizes, a study similar to this—Tol (2023b) shows that clustering is even more pronounced in other disciplines—could consider the actual nominees as well as the composition and deliberations of the prize committees.

The second gap is that the network used is the network of *formal* advisory relationships. *Informal* mentoring is just as important but hard to document for people who did not leave an autobiography, extensive correspondence, or in-depth interviews. The co-authorship network may be important too—data were not collected for this paper (see Molina et al., 2021, for an analysis of the co-author network of Nobelists)—after careful controlling for changes over time in publication norms and cultures and the size of the economics profession.

The third, and arguably most important gap is the candidacy. The results above are all conditional on having established a track record that is Nobel-worthy. The current paper is silent on the question how to become Nobel-worthy—see Korom (2021) for an attempt. In future research, a long list could be created of everyone who has published in a Top 5 journal or every economist with a paper with over 1,000 citations—perhaps supplemented with semantic analysis (Iaria et al., 2018) or citation analysis (Uzzi et al., 2013) to capture novelty—and use that to test, perhaps using synthetic control (Chan et al., 2014), what it takes to progress from not-impossible to a plausible candidate.

It is an open question how the networks of Nobel candidates differ from other economists—particularly to what extent excellent people group together, in departments and co-author networks, and how such social dynamics propel researchers to new heights. This can be studied as more data become available, not just for the very top, but for many others through online CVs, LinkedIn and IDEAS/RePEc. These issues are postponed for future research.

Appendix A. Family relationships

A.1. Nobel professors

Nobelists who won after their Nobel professors:

- Koopmans (1975) after Tinbergen (1969)
- Friedman (1976) after Kuznets (1971)
- Klein (1980) after Samuelson (1970)
- Solow (1987) after Leontief (1973)
- Haavelmo (1989) after Frisch (1969)
- Markowitz (1990) after Friedman (1976)
- Fogel (1993) after Kuznets (1971)

[13] If that is what they do. I used my first spell as a nominator to argue for Thomas Schelling, my second spell to argue for Anne Krueger. The Nobel laureates closest to my own research are William Nordhaus and Robert Wilson.

[14] For instance, it may seem peculiar that there is a Nobel prize for discrete choice but not for two-stage least squares, a method that is used more widely. It is not peculiar for those who know.

- Harsanyi (1994) after Arrow (1972)
- Mirrlees (1996) after Stone (1984)
- Merton (1997) after Samuelson (1970)
- Scholes (1997) after Miller (1990)
- Akerlof (2001) after Solow (1987)
- Smith (2002) after Leontief (1973)
- Schelling (2005) after Leontief (1973)
- Phelps (2006) after Tobin (1981)
- Maskin (2007) after Arrow (1972)
- Myerson (2007) after Arrow (1972)
- Williamson (2009) after Simon (1978)
- Diamond (2010) after Solow (1987)
- Fama (2013) after Miller (1990)
- Hansen (2013) after Sims (2011)
- Shiller (2013) after Modigliani (1985)
- Tirole (2014) after Maskin (2007)
- Deaton (2015) after Stone (1984)
- Nordhaus (2018) after Solow (1987)
- Romer (2018) and Lucas (1995)
- Banerjee (2019) after Maskin (2007)

A.2. Nobel students

Nobelists who won after their Nobel students:

- Allais (1988) after Debreu (1983)
- Leontief (1973) after Samuelson (1970)
- Schelling (2005) after Spence (2001)
- Hurwicz (2007) after McFadden (2000)
- Fama (2013) after Scholes (1997)
- Wilson (2020) after Roth (2012) and Holmstrom (2016)
- Angrist (2021) after Duflo (2019)

A.3. Nobel peers

Nobelists who won after their Nobel peers:

- Ohlin (1977) after Myrdal (1974)
- Simon (1978) after Friedman (1976)
- Tobin (1981) after Samuelson (1970)
- Stone (1984) after Meade (1977)
- Buchanan (1986) after Stigler (1982)
- Solow (1987) after Samuelson (1970)
- Markowitz (1990) after Modigliani (1985)
- Coase (1991) after Stigler (1982) and Buchanan (1986)
- Fogel (1993) after Friedman (1976)
- Lucas (1995) after Becker (1992)
- Merton (1997) after Klein (1980)
- Stiglitz (2001) after Sen (1998)
- Smith (2002) after Samuelson (1970) and Solow (1987)
- Schelling (2005) after Samuelson (1970), Solow (1987) and Smith (2002)
- Hurwicz (2007) after Modigliani (1985) and Markowitz (1990)
- Eric Maskin (2007) after Harsanyi (1994)
- Roger Myerson (2007) after Harsanyi (1994)
- Diamond (2010) after Akerlof (2001)
- Mortensen (2010) after Prescott (2004)
- Shapley (2012) after Nash (1994)
- Deaton (2015) after Mirrlees (1996)
- Holmstrom (2016) after Roth (2012)
- Nordhaus (2018) after Akerlof (2001) and Diamond (2010)
- Banerjee (2019) after Tirole (2014)

- Milgrom (2020) after Roth (2012) and Holmstrom (2016)

Additional material

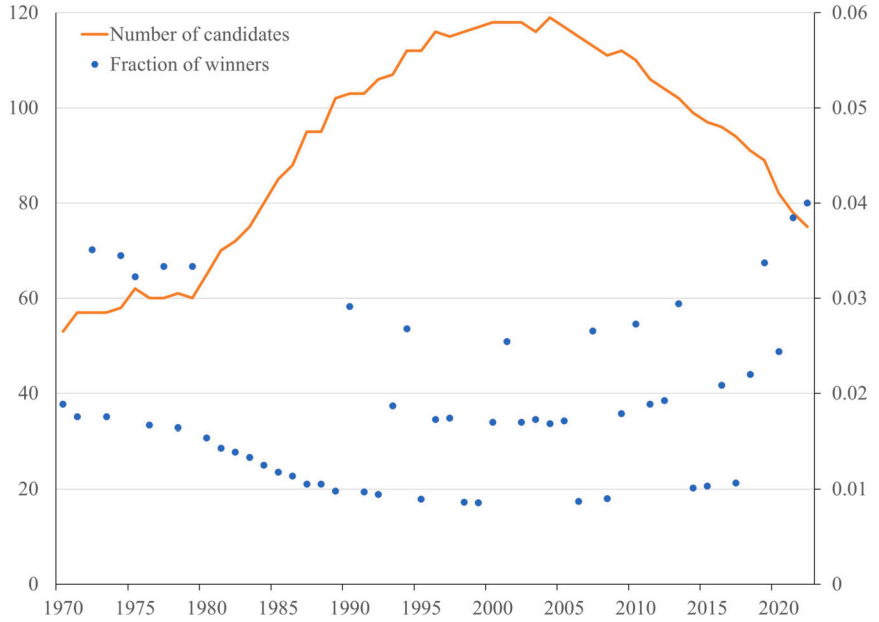

Fig. A.1. The number of Nobel candidates (solid line, left axis) and the fraction that one (dots, right axis) per year.

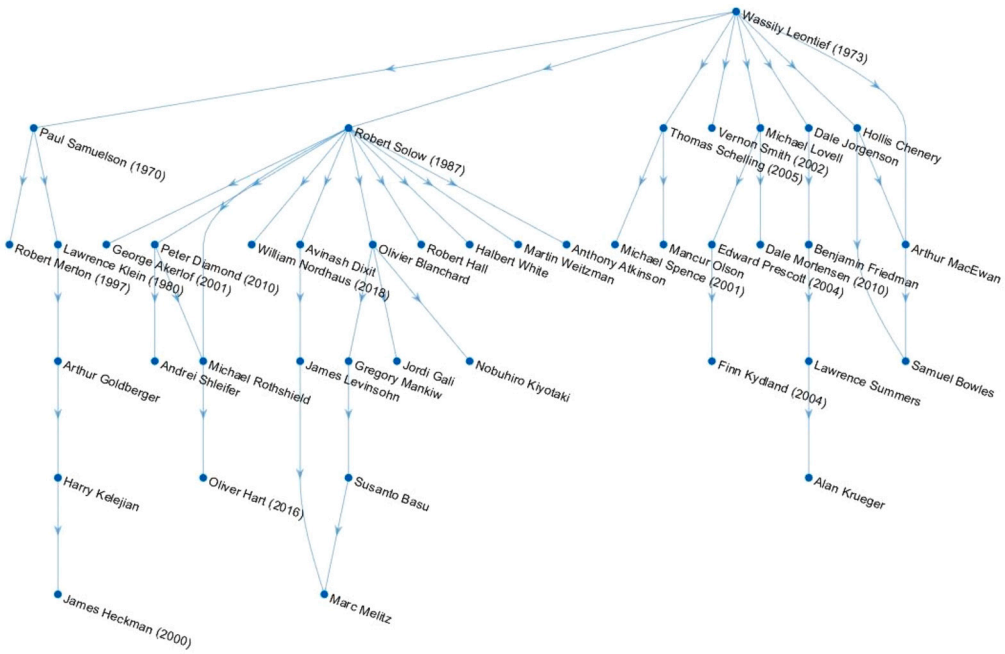

Fig. A.2. Academic descendants of Leontief.

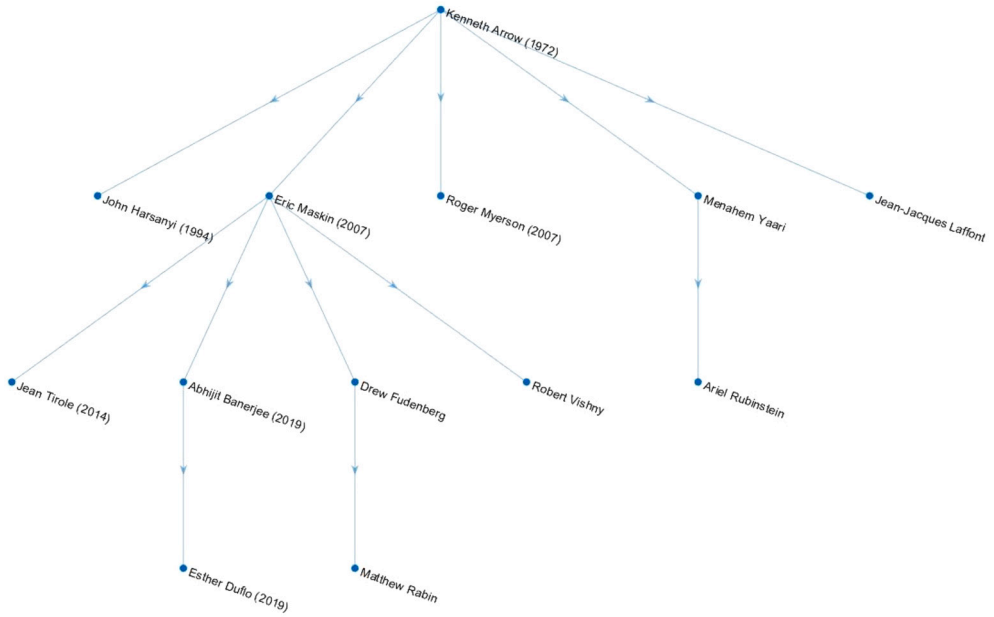

Fig. A.3. Academic descendants of Arrow.

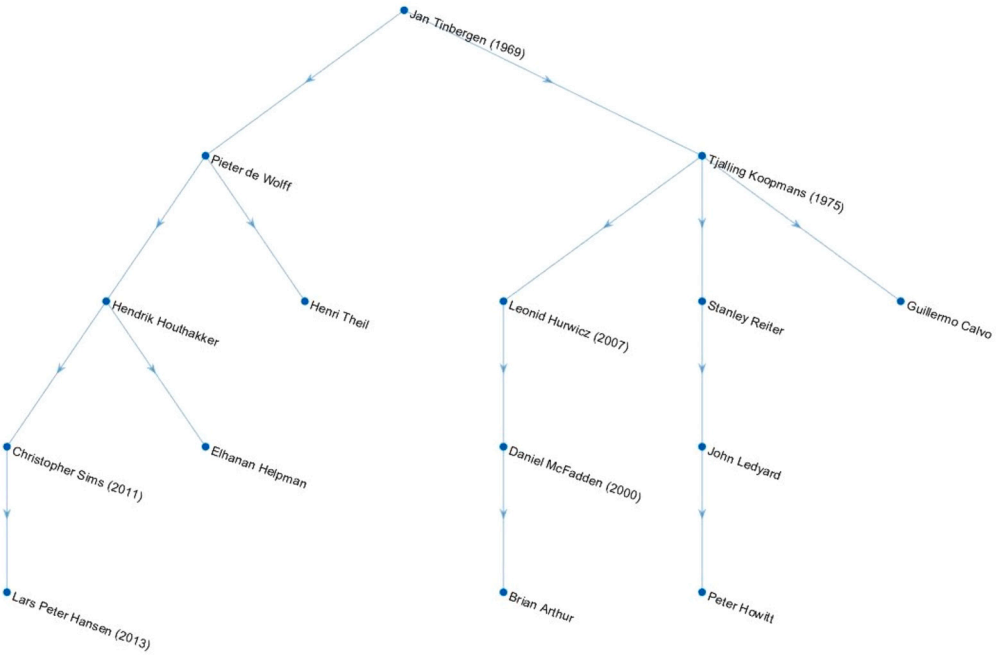

Fig. A.4. Academic descendants of Tinbergen.

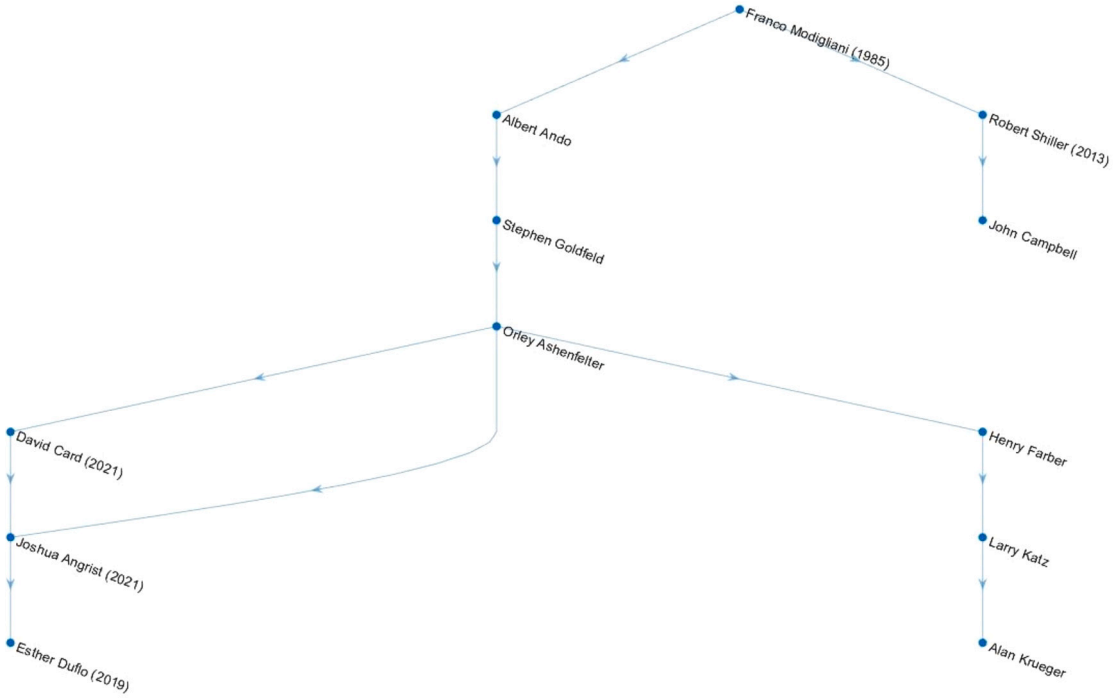

Fig. A.5. Academic descendants of Modigliani.

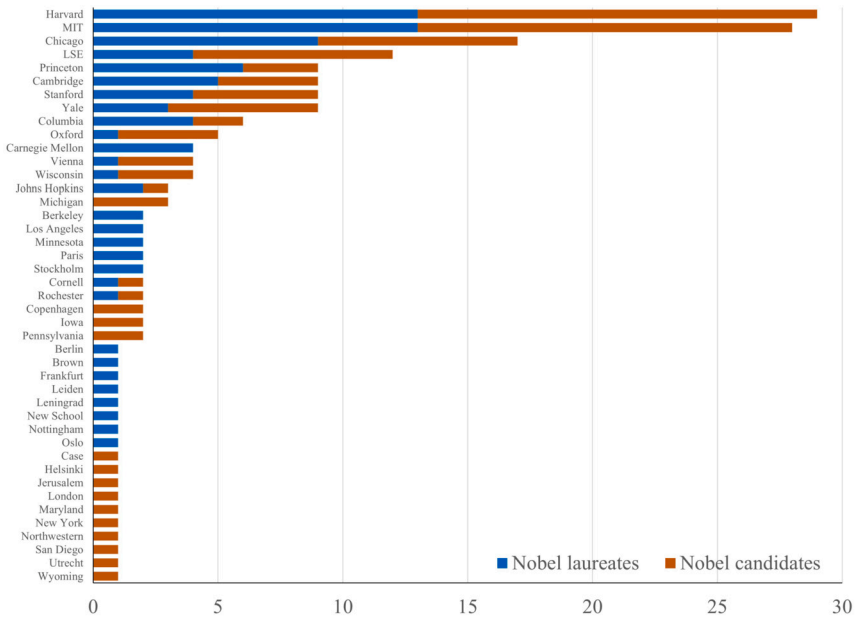

Fig. A.6. Nobel laureates and candidates by alma mater.

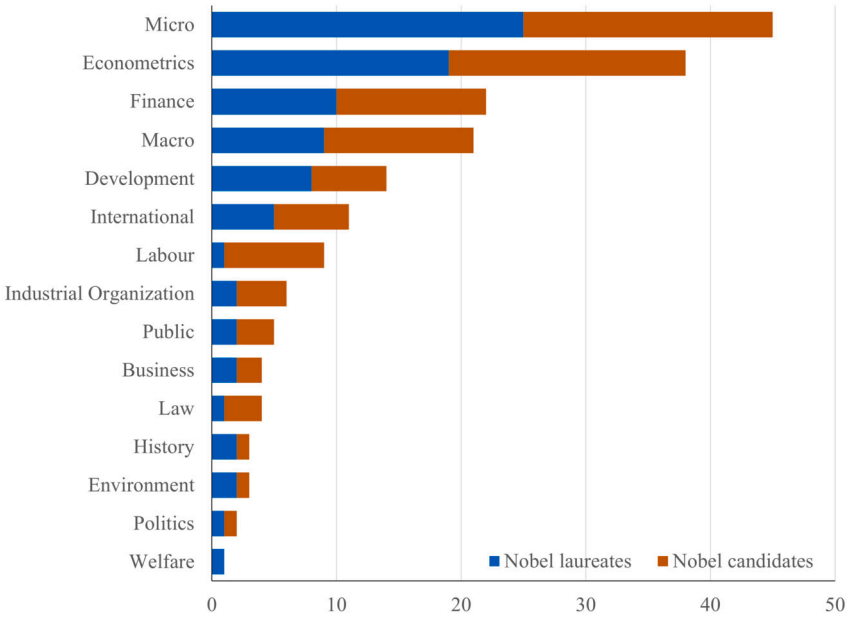

Fig. A.7. Nobel laureates and candidates by specialisation.

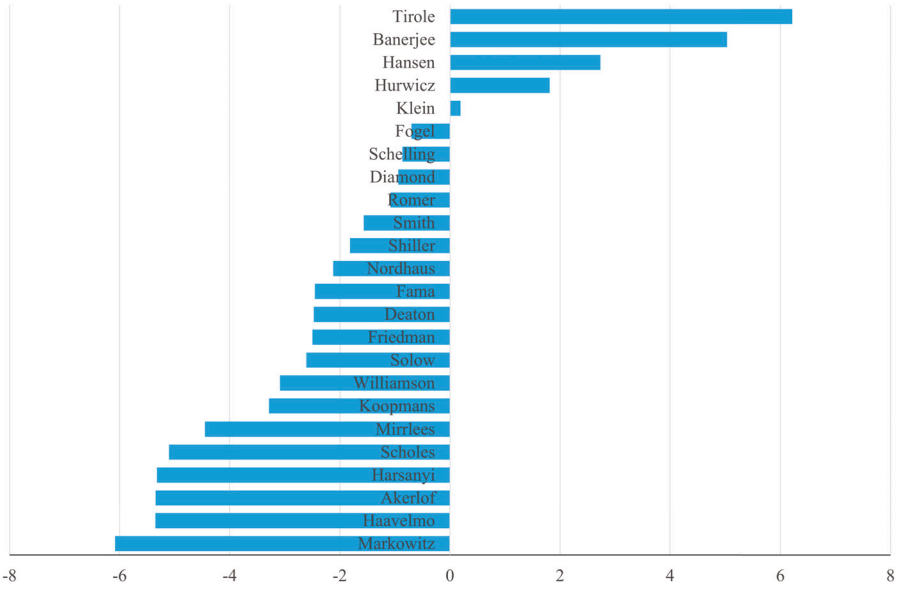

Fig. A.8. The t-statistic of the impact of a professor winning the Nobel prize on the annual citation numbers of his student who won the Nobel prize after him.

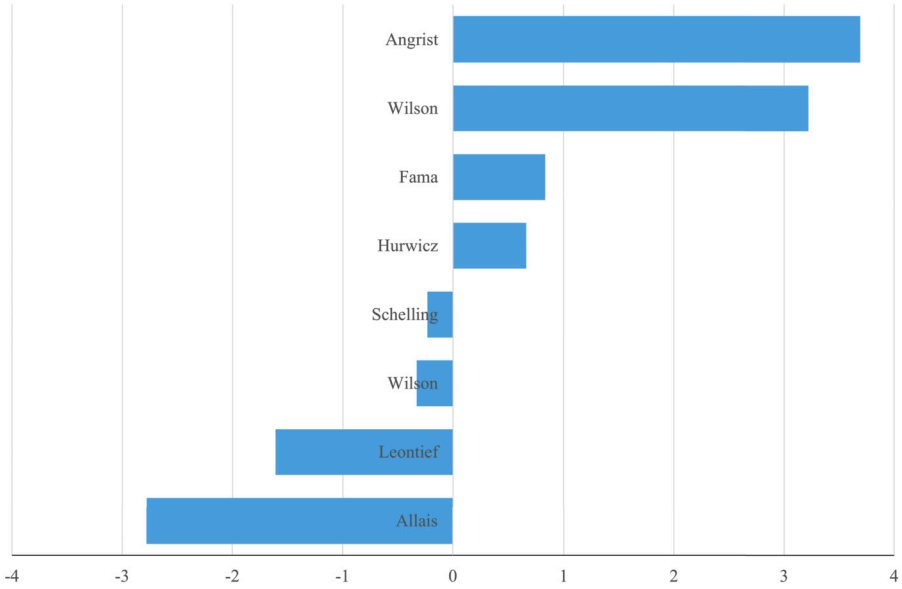

Fig. A.9. The t-statistic of the impact of a student winning the Nobel prize on the annual citation numbers of his or her professor who won the Nobel prize after him or her.

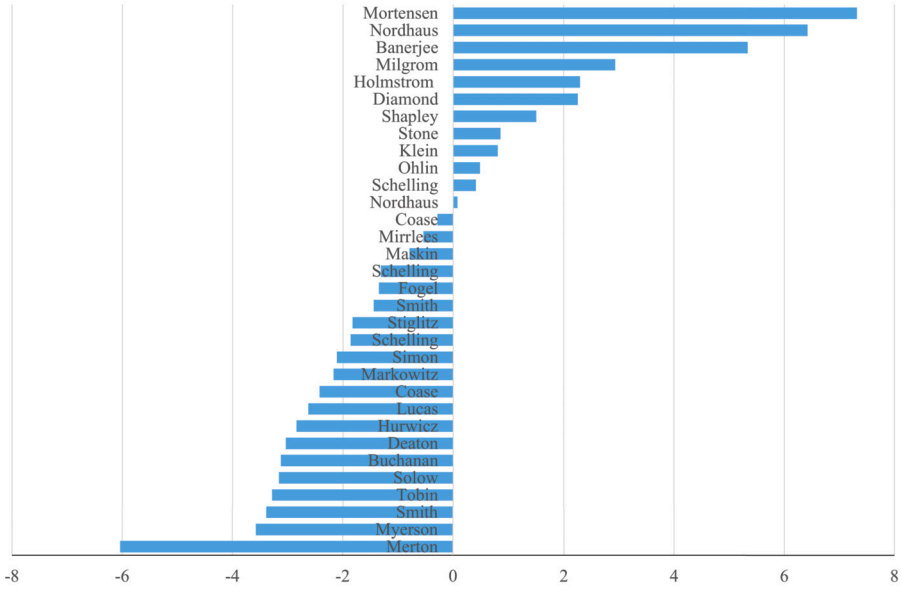

Fig. A.10. The t-statistic of the impact of a student winning the Nobel prize on the annual citation numbers of his fellow student who won the Nobel prize after him.

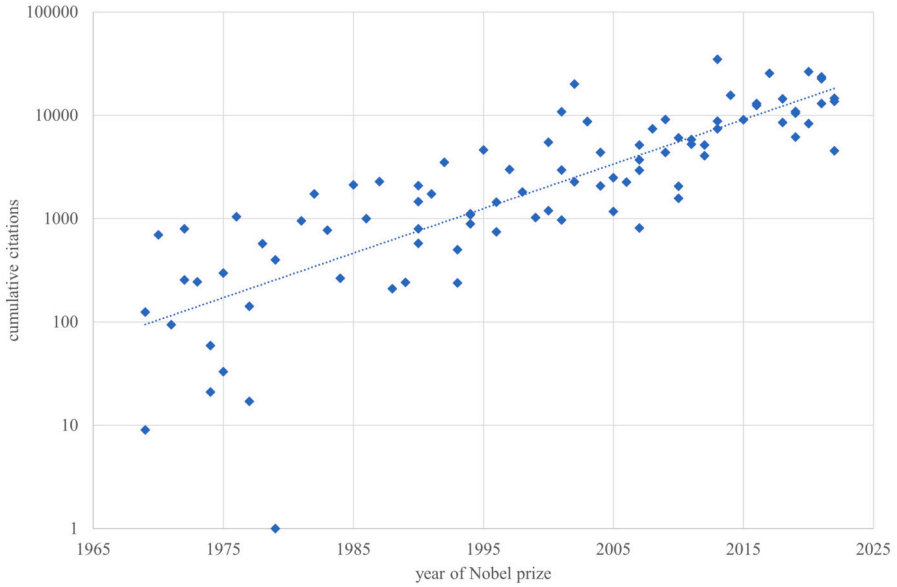

Fig. A.11. Cumulative citations (vertical axis) at the time of the Nobel award (horizontal axis) for all Laureates.

Table A.1
Nobel laureates and candidates.

ID	name	birth	death	won	alma mater	JEL	source
1	Ragnar Frisch	1895	1973	1969	Oslo	E	-
2	Jan Tinbergen	1903	1994	1969	Leiden	E	-
3	Paul Samuelson	1915	2009	1970	Harvard	C	-
4	Simon Kuznets	1901	1985	1971	Columbia	O	-
5	John Hicks	1904	1989	1972	Oxford	C	-
6	Kenneth Arrow	1921	2017	1972	Columbia	D	-
7	Wassily Leontief	1905	1999	1973	Berlin	C	-
8	Gunnar Myrdal	1898	1987	1974	Stockholm	E	-
9	Friedrich Hayek	1899	1992	1974	Vienna	P	-
10	Tjalling Koopmans	1910	1985	1975	Leiden	C	-
11	Leonid Kantorovich	1912	1986	1975	Leningrad	C	-
12	Milton Friedman	1912	2006	1976	Columbia	E	-
13	Bertil Ohlin	1899	1979	1977	Stockholm	F	-
14	James Meade	1907	1995	1977	Cambridge	F	-
15	Herbert Simon	1916	2001	1978	Chicago	L	-
16	Theodore Schultz	1902	1998	1979	Wisconsin	O	-
17	Arthur Lewis	1915	1991	1979	LSE	O	-
18	Lawrence Klein	1920	2013	1980	MIT	C	-
19	James Tobin	1918	2002	1981	Harvard	G	-
20	George Stigler	1911	1991	1982	Chicago	D	-
21	Gerard Debreu	1921	2004	1983	Paris	D	-
22	Richard Stone	1913	1991	1984	Cambridge	E	-
23	Franco Modigliani	1918	2003	1985	New School	G	-
24	James Buchanan	1919	2013	1986	Chicago	H	-
25	Robert Solow	1924		1987	Harvard	O	-
26	Maurice Allais	1911	2010	1988	Paris	D	-
27	Trygve Haavelmo	1911	1999	1989	Oslo	C	-
28	Merton Miller	1923	2000	1990	Johns Hopkins	G	-
29	Harry Markowitz	1927		1990	Chicago	G	-
30	William Sharpe	1934		1990	Los Angeles	G	-
31	Ronald Coase	1910	2013	1991	LSE	K	-
32	Gary Becker	1930	2014	1992	Chicago	D	-
33	Douglas North	1920	2015	1993	Berkeley	N	-
34	Robert Fogel	1926	2013	1993	Johns Hopkins	N	-
35	John Harsanyi	1920	2000	1994	Stanford	C	-
38	Robert Lucas	1937		1995	Chicago	E	-
39	William Vickrey	1914	1996	1996	Columbia	D	-
40	James Mirrlees	1936	2018	1996	Cambridge	D	-

Table A.1 (*continued*)

ID	name	birth	death	won	alma mater	JEL	source
41	Myron Scholes	1941		1997	Chicago	G	-
42	Robert Merton	1944		1997	MIT	G	-
43	Amartya Sen	1933		1998	Cambridge	D	-
44	Robert Mundell	1932	2021	1999	MIT	E	-
45	Daniel McFadden	1937		2000	Minnesota	C	-
46	James Heckman	1944		2000	Princeton	C	-
47	George Akerlof	1940		2001	MIT	D	-
48	Michael Spence	1943		2001	Harvard	D	-
49	Joseph Stiglitz	1943		2001	MIT	D	-
50	Vernon Smith	1927		2002	Harvard	D	-
51	Daniel Kahneman	1934		2002	Berkeley	D	-
52	Clive Granger	1934	2009	2003	Nottingham	C	-
53	Robert Engle	1942		2003	Cornell	C	-
54	Edward Prescott	1940		2004	Carnegie Mellon	E	-
55	Finn Kydland	1943		2004	Carnegie Mellon	E	-
56	Thomas Schelling	1921	2016	2005	Harvard	C	-
57	Robert Aumann	1930		2005	MIT	C	-
58	Edmund Phelps	1933		2006	Yale	E	-
59	Leonid Hurwicz	1917	2008	2007	LSE	D	-
60	Eric Maskin	1950		2007	Harvard	D	-
61	Roger Myerson	1951		2007	Harvard	D	-
62	Paul Krugman	1953		2008	MIT	F	-
63	Oliver Williamson	1932	2020	2009	Carnegie Mellon	H	-
64	Elinor Ostrom	1933	2012	2009	Los Angeles	Q	-
65	Dale Mortensen	1939	2014	2010	Carnegie Mellon	D	-
66	Peter Diamond	1940		2010	MIT	D	-
67	Christopher Pissarides	1948		2010	LSE	D	-
68	Christopher Sims	1942		2011	Harvard	M	-
69	Thomas Sargent	1943		2011	Harvard	M	-
70	Lloyd Shapley	1923	2016	2012	Princeton	C	-
72	Eugene Fama	1939		2013	Chicago	G	-
73	Robert Shiller	1946		2013	MIT	F	-
74	Lars Peter Hansen	1952		2013	Minnesota	F	-
75	Jean Tirole	1953		2014	MIT	L	-
76	Angus Deaton	1945		2015	Cambridge	I	-
77	Oliver Hart	1948		2016	Princeton	D	-
78	Bengt Holmstrom	1949		2016	Stanford	D	-
79	Richard Thaler	1945		2017	Rochester	D	-
80	William Nordhaus	1941		2018	MIT	Q	-
81	Paul Romer	1955		2018	Chicago	O	-
82	Abhijit Banerjee	1961		2019	Harvard	O	-
83	Michael Kremer	1964		2019	Harvard	O	-
84	Esther Duflo	1972		2019	MIT	O	-
85	Robert Wilson	1937		2020	Harvard	D	-
86	Paul Milgrom	1948		2020	Stanford	D	-
87	David Card	1956		2021	Princeton	J	-
88	Joshua Angrist	1960		2021	Princeton	C	-
89	Guido Imbens	1963		2021	Brown	C	-
183	Ben Bernanke	1953		2022	MIT	E	
151	Douglas Diamond	1953		2022	Yale	G	
184	Philip Dybvig	1955		2022	Yale	G	
90	Ludwig von Mises	1881	1973		Vienna	P	ad hoc
91	Frank Knight	1882	1972		Cornell	D	ad hoc
92	Alvin Hansen	1887	1975		Wisconsin	E	ad hoc
93	Harold Hotelling	1895	1973		Princeton	C	ad hoc
185	Roy Harrod	1900	1978		Cambridge	E	ad hoc
94	Oskar Morgenstern	1902	1977		Vienna	D	ad hoc
95	Abba Lerner	1903	1982		LSE	D	ad hoc
96	Joan Robinson	1903	1983		Cambridge	E	ad hoc
97	Ester Boserup	1910	1999		Copenhagen	O	ad hoc
98	Edith Penrose	1914	1996		Johns Hopkins	M	ad hoc
99	Lionel McKenzie	1919	2010		Princeton	D	ad hoc
71	Alvin Roth	1951		2012	Stanford	D	-
100	William Baumol	1922	2017		LSE	J	Clarivate
101	Gordon Tullock	1922	2014		Chicago	K	Clarivate
102	William Meckling	1922	1998		Chicago	G	ad hoc
103	Jacob Mincer	1922	2006		Columbia	J	ad hoc
186	Kelvin Lancaster	1924	1999		London	D	ad hoc
104	Henri Theil	1924	2000		Utrecht	C	ad hoc

(*continued on next page*)

Table A.1 (*continued*)

ID	name	birth	death	won	alma mater	JEL	source
190	Richard Easterlin	1926			Pennsylvania	O	Clarivate
105	Harold Demsetz	1930	2019		Northwestern	K	Clarivate
106	Israel Kirzner	1930			New York	L	Clarivate
107	Wayne Fuller	1931			Iowa	C	Clarivate
191	Richard Layard	1934			LSE	J	Clarivate
187	Mancur Olson	1932	1998		Maryland	D	ad hoc
108	Dale Jorgenson	1933	2022		Harvard	E	Clarivate
109	Jagdish Bhagwati	1934			MIT	F	Clarivate
110	Anne Krueger	1934			Wisconsin	H	Clarivate
111	Amos Tversky	1937	1996		Michigan	D	ad hoc
112	Fischer Black	1938	1995		Harvard	G	ad hoc
193	Samuel Bowles	1939			Harvard	D	Clarivate
113	Martin Feldstein	1939	2019		Oxford	E	Clarivate
114	Michael Jensen	1939			Chicago	G	Clarivate
115	Soren Johansen	1939			Copenhagen	C	Clarivate
116	Richard Posner	1939			Harvard	K	Clarivate
194	Herbert Gintis	1940			Harvard	D	Clarivate
117	Sam Peltzman	1940			Chicago	H	Clarivate
118	Stewart Myers	1940			Stanford	G	Clarivate
119	Guillermo Calvo	1941			Yale	E	ad hoc
120	Evan Porteus	1942			Case	D	ad hoc
121	Martin Weitzman	1942	2019		MIT	Q	Clarivate
122	Robert Hall	1943			MIT	E	Clarivate
123	Mark Granovetter	1943			Harvard	D	Clarivate
124	Katarina Juselius	1943			Helsinki	C	Clarivate
125	Robert Barro	1944			Harvard	E	Clarivate
126	Avinash Dixit	1944			MIT	D	Clarivate
127	David Hendry	1944			LSE	C	Clarivate
128	Stephen Ross	1944	2017		Harvard	G	Clarivate
129	Anthony Atkinson	1944	2017		Cambridge	D	Clarivate
130	Brian Arthur	1945			Michigan	D	Clarivate
131	David Dickey	1945			Iowa	C	Clarivate
132	Jerry Hausman	1946			Oxford	C	Clarivate
133	Elhanan Helpman	1946			Harvard	F	Clarivate
134	Hashem Pesaran	1946			Cambridge	C	Clarivate
135	John Taylor	1946			Stanford	E	Clarivate
136	Claudia Goldin	1946			Chicago	J	Clarivate
137	Francine Blau	1946			Harvard	J	ad hoc
138	Joel Mokyr	1946			Yale	N	Clarivate
139	Jean-Jacques Laffont	1947	2004		Harvard	L	ad hoc
140	Edward Lazear	1948	2020		Harvard	J	Clarivate
141	Olivier Blanchard	1948			MIT	E	Clarivate
142	Peter Phillips	1948			LSE	C	Clarivate
143	Charles Manski	1948			MIT	C	Clarivate
144	David Teece	1948			Pennsylvania	L	Clarivate
145	Ariel Pakes	1949			Harvard	C	Clarivate
146	David Kreps	1950			Stanford	D	Clarivate
147	Halbert White	1950	2012		MIT	C	Clarivate
148	Ariel Rubinstein	1951			Jerusalem	C	Clarivate
149	Mark Gertler	1951			Stanford	E	Clarivate
150	Richard Blundell	1952			LSE	J	Clarivate
192	Andrew Oswald	1953			Oxford	J	Clarivate
152	Kenneth Rogoff	1953			MIT	G	Clarivate
153	Sanford Grossman	1953			Chicago	G	ad hoc
154	John Moore	1954			LSE	G	Clarivate
155	Kenneth French	1954			Rochester	G	Clarivate
156	David Audretsch	1954			Wisconsin	L	Clarivate
157	Gene Grossman	1955			MIT	F	Clarivate
158	Nobuhiro Kiyotaki	1955			Harvard	G	Clarivate
159	George Loewenstein	1955			Yale	D	Clarivate
160	Carmen Reinhart	1955			Columbia	F	Clarivate
161	Philippe Aghion	1956			Harvard	O	Clarivate
162	Ernst Fehr	1956			Vienna	D	Clarivate
163	Manuel Arellano	1957			LSE	C	Clarivate
164	Daniel Levinthal	1957			Stanford	M	Clarivate
165	Alberto Alesina	1957	2020		Harvard	H	Clarivate
166	Kevin Murphy	1958			Chicago	D	Clarivate
167	James Levinsohn	1958			Princeton	F	Clarivate
168	Tim Bollerslev	1958			San Diego	C	IDEAS/RePEc

Table A.1 (*continued*)

ID	name	birth	death	won	alma mater	JEL	source
169	John Campbell	1958			Yale	G	IDEAS/RePEc
170	Stephen Berry	1959			Wisconsin	C	Clarivate
171	Pierre Perron	1959			Yale	C	Clarivate
172	Colin Camerer	1959			Chicago	D	Clarivate
173	Robert Vishny	1959			MIT	G	IDEAS/RePEc
174	Alan Krueger	1960	2019		Harvard	J	Clarivate
198	James Robinson	1960			Yale	O	Clarivate
175	Jordi Gali	1961			MIT	E	Clarivate
176	Andrei Shleifer	1961			MIT	G	IDEAS/RePEc
177	Stephen Bond	1963			Oxford	C	Clarivate
189	Simon Johnson	1963			MIT	O	Clarivate
178	Raghuram Rajan	1963			MIT	E	Clarivate
179	Matthew Rabin	1963			MIT	D	Clarivate
180	Daron Acemoglu	1967			LSE	O	Clarivate
181	Marc Melitz	1968			Michigan	F	Clarivate
182	John List	1968			Wyoming	D	Clarivate

Table A.2
Summary statistics.

Variable	Mean	Std. Dev.	Min.	Max.	N
Nobelist	0.018	0.134	0	1	4952
Distance to Nobel ...					
... Professors	0.004	0.046	0	1	4952
... Students	0.174	0.242	0	1	4952
... Peers	0.039	0.09	0	1	4952
Female	0.061	0.24	0	1	4952

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