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Nobel students beget Nobel professors

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By Richard S.J. Tol*

It is unclear whether the hierarchy in the economics profession is the result of the agglomeration of excellence or of nepotism. 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 not *significantly more or less likely to win. Professors of Nobel Prize winners, however, are significantly more likely to win.*
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A Nobel Prize begets Nobel Prizes, or so the story goes. The departmental, collegial and personal concentration of winners of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel is extraordinary (Tol, 2022). This can be seen as clusters of quality: The best professors come together in the best schools (Ellison, 2013), inspire, teach and stimulate each other (Azoulay, Zivin and Wang, 2010; Borjas and Doran, 2012; Bosquet and 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, Linnemer and Visser, 2008; Hamermesh and Schmidt, 2003; Laband and Piette, 1994; Medoff, 2003; Carrell, Figlio and Lusher, 2022). The Prize Committee solicits nominations from a randomly selected sample of professors of economics[1] *and all living Laureates* (Zuckerman, 1996), who may put their proteges forward. 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.

Tol (2022) builds the network of professor-student relations for the Nobel laureates in economics. There are 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 four grand-professors, one great-grand-professor, one great-great-grand-professor,

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[1] actually, a sample outside Sweden and all professors in Sweden

and one great-great-great-grand-professor. Duflo also illustrates that close familial ties[2] did not stop her from revolutionizing economic methodology. Clustering does not stop innovation.

Besides data on the Nobelists, I also collect data on the candidates for the Nobel Prize—those economists who have published papers that are highly-cited in economics journals—and connect them, if possible, to the Nobel family tree. 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 *professor* does *not* affect the probability of winning the Nobel prize, although (s)he may win it sooner. However, having a Nobelist as a *student* significantly and substantially increases the probability of winning.

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 changed in one particular way. That is, changes in a network can be analyzed using standard selection models.

The paper proceeds as follows. Section I discusses the data and methods used. Section II presents the results. Section III concludes.

I. Data and methods

A. Data

The 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. The network therefore also includes more general mentor-mentee or professor-student relations. Tol (2022) describes in greater detail how these data were collected, including the uncertainties where relationships were unclear. 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, 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,

[2] she is also married to a Nobelist

arguing that economics should be an empirical science just as it turned to theory.[3] 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 typically measure in the tens of thousands, concentrated on a few seminal papers. Clarivate's Citation Laureates meet these criteria and indeed many Citation Laureates later won the Nobel prize.

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, Daron Acemoglu, John Campbell and Robert Vishny.[4] 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.[5] 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, Evan Porteus is not. Michael Jensen is a Citation Laureate, but 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 sticky prices, general equilibrium, labour, and two-stage least squares, 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 1 in the Appendix.

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.

For every Laureate and candidate, I collected year of birth, year of death (if appropriate), the year of winning, gender, *alma mater*, and one-digit JEL classifier

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

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

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

using Wikipedia as the main source of information. 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, 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.[6]

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

B. *Methods*

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

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

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 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 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).

[6]Jan Tinbergen was the student and grandstudent of two prominent physicists, Ehrenfest and Boltzmann, who did not won 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 from a medicine laureate (Sherrington).

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. The total number of points is then divided by the total number of laureates.

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. As a sensitivity check, I also consider $h = -0.5$ and $h = -2$. Proximity is defined as long as $h < 0$. As h gets smaller, greater emphasis is placed on closer ties.

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) I also measure horizontal closeness. Students of the same professor (academic siblings) score 1, those with a shared grandprofessor (academic cousins) score 2, and so on. One shared professor counts the same as two or more shared professors. I take the minimum of this measure, so one shared professor counts the same as one shared professor and, via two non-shared professors, one shared grandprofessor.

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

II. Results

Table 1 shows the results of eight regressions. 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; Arrow, Solow and Samuelson also have three Nobel students, Leontief has four.) 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.

Figure 1 shows 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. The effect size is substantial. Those candidates without Nobel students have a predicted annual win probability of 7% or less. This probability is over 30% for those who are closest to Nobel descendants, more than a fourfold increase.

Distance to Nobel professors is positive but insignificant: Students of Nobel laureates are not more likely to win.

The inclusion of fixed effects for the *alma mater* does not change the results in a meaningful way. Observations are dropped because some universities have candidates but no winners. Most of the dummy variables for the remaining universities are statistically insignificant. Yale has a negative coefficient, with a p-value of 2.1% (logit) or 2.6% (probit).

Field fixed effects again leave the main results unaffected. The only significant dummy is for JEL-code O–Economic Development and Growth. Researchers in this field are significantly more 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, except when *alma mater* fixed effects are included. It is only weakly significant in that case. Although there are claims to the contrary, women are not discriminated against in this regard.

Table 2 sheds some light on the mechanism. Proximity to Nobel professors remains positive but insignificant when I distinguish between living and deceased professors. The effect size is larger for *deceased* professors. (Don't get any ideas, guys!) This argues against the explanation that it is nominations of previous Laureates that make you win the Nobel Prize. Rather, it takes time for a brilliant paper to prove itself, to have demonstrably revolutionized a substantial part of the profession, a necessary condition for winning the Nobel Prize. Therefore, people tend to win later in life, increasing the probability that their PhD advisor has passed. The effect is weak, however. The same results is found when I split distance to Nobel professors between those who won in the last decade and those who won more than 10 years ago. The impact of older Nobel professors is weakly significant, the impact of more recent laureates is insignificant.

It may be that nominations by Nobel students are important. However, no one has won the Nobel Prize after a student has won and died, and professors win within 10 years of their Nobel students. I therefore cannot test this hypothesis.

Table 3 varies the parameter h in Equation (1). The middle columns have $h = -1$ as in the other tables. In the left columns, $h = -0.5$ so that weight is shifted to more distant relationships. Coefficients are no longer statistically significantly different from zero. In the right columns, $h = -2$ so that more emphasis is placed on closer relationships. The impact of proximity to Nobel professors is not significant whereas the effect of Nobel students is. The result for students is in line with casual observations: No one has won the Nobel Prize after a grandstudent did. The result for professors underlines a key result: Nobel ancestry is unimportant.

The right-most column of Table 3 adds proximity to academic siblings who previously won the Nobel prize. This is significant at the 10% level. Inclusion does not affect the estimates for proximity to Nobel students but the estimated coefficient for Nobel professors shrinks while its p-value grows. This suggests that there are clusters of excellence around some professors, only some of whom are Nobel laureates themselves. The evidence is weak, however.

Table 4 restricts the number of candidates, first by excluding the candidates identified by me and denoted as “ad hoc” in Table 1, and then by excluding those as well as the candidates found at IDEAS/RePEc. Fewer candidates mean that the average probability of winning goes up. It does materially affect the results. Effect size and significance are almost the same in the limited samples as in the full sample.

Table 4 also shows a regression with individual fixed effects. Here, all the (hitherto) unsuccessful candidates are dropped from the regression,[7] as the fixed effect perfectly predicts their lack of success. Proximity to Nobel students is highly significant, proximity to Nobel professors weakly so. As this regression only contains the winners, the positive coefficient on proximity thus means that you win *sooner* if you have a Nobel laureate as your student.

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. 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.[8] 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.[9]

III. 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* of Nobelists are more likely to win but the impact on their *students* is insignificant. The impact of Nobel professors remains insignificant if the sample is

[7] The same would happen if the data were seen as a panel.

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

[9] 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.

limited to recent winners or living winners, and if the distance measure emphasizes close relationships. There is no evidence of successful lobbying of Nobelists on behalf of their students. However, Nobelists lobbying for their professors cannot be excluded. In sum, your best bet to win a Nobel prize is to make sure your 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. 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 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-worth. It is an open question how the networks of Nobel candidates differ from other economists—particularly to what extent excellent people group together and how social dynamics propel researchers to new heights.

These issues are postponed to future research. For know, as Graham Nash wrote, teach your children well, it may win you a Nobel prize.

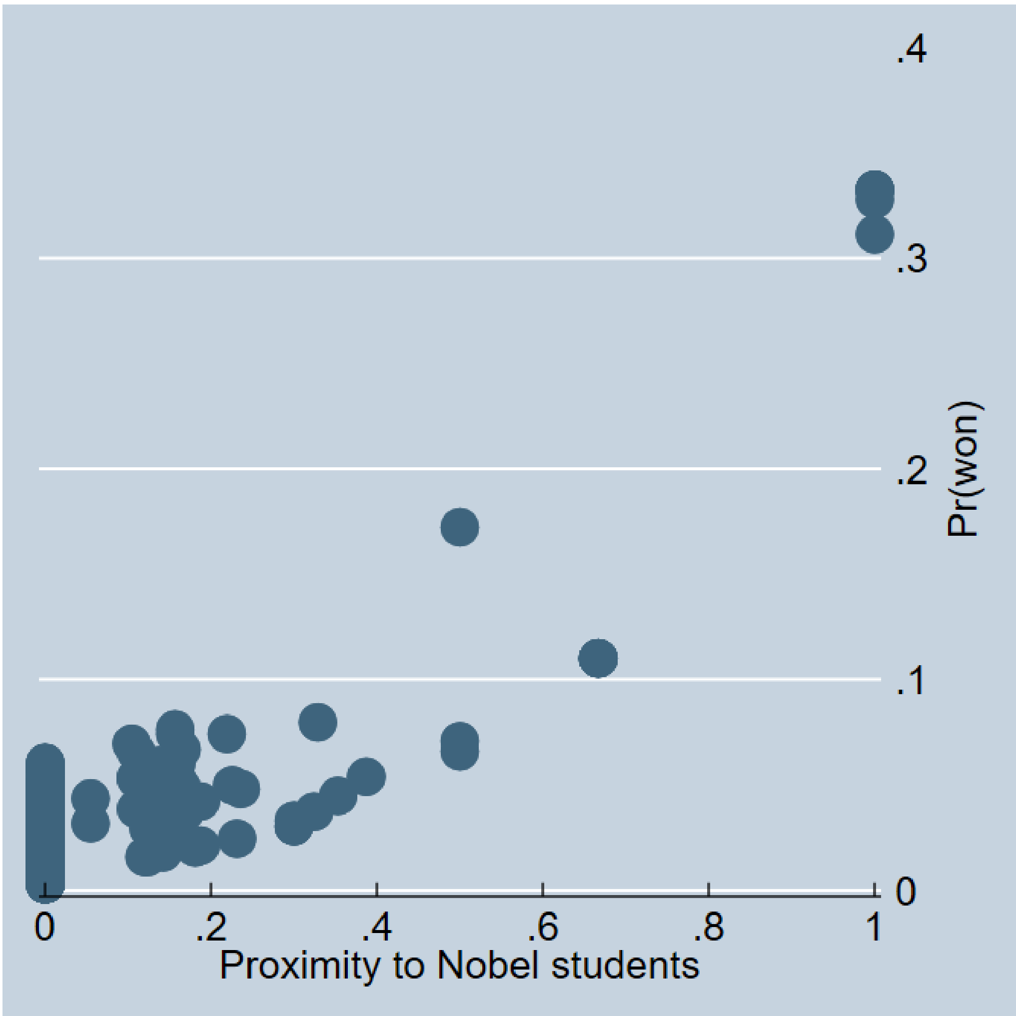

FIGURE 1. PROBABILITY, CONDITIONAL ON BEING A CANDIDATE, OF WINNING THE NOBEL PRIZE IN ECONOMICS AS A FUNCTION OF THE RELATIVE PROXIMITY TO A PREVIOUSLY ENNOBELED STUDENT.

Note: Predicted probability according to the logit model with year fixed effects. See Table 1.

Table 1—Probability of winning the Nobel Prize with alternative fixed effects.

	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Female	-1.015	-0.387	-1.032	-0.411	-1.705*	-0.697*	-1.039	-1.039
	(-1.41)	(-1.49)	(-1.43)	(-1.54)	(-2.11)	(-2.13)	(-1.39)	(-1.39)
Proximity to Nobel professors	0.575	0.244	0.598	0.243	0.567	0.207	0.511	0.511
	(1.40)	(1.44)	(1.45)	(1.40)	(1.12)	(0.99)	(1.15)	(1.15)
Proximity to Nobel students	3.322***	1.816***	3.713***	1.885***	5.017**	2.342**	3.858***	3.858***
	(4.19)	(4.08)	(3.54)	(3.76)	(3.26)	(3.12)	(3.35)	(3.35)
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
Individual fixed effects	No	No	No	No	No	No	No	No
Observations	4508	4508	4508	4508	3975	3975	4460	4460

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

TABLE 2—PROBABILITY OF WINNING THE NOBEL PRIZE FOR DIFFERENT TYPES OF NOBELISTS.

	Logit	Probit	Logit	Probit	Logit	Probit
Female	-1.032	-0.411	-1.033	-0.408	-1.033	-0.408
	(-1.43)	(-1.54)	(-1.43)	(-1.53)	(-1.43)	(-1.53)
Proximity to Nobel students	3.713***	1.885***	3.592***	1.833***	3.592***	1.833***
	(3.54)	(3.76)	(3.43)	(3.64)	(3.43)	(3.64)
Proximity to Nobel professors	0.598	0.243				
	(1.45)	(1.40)				
Proximity to deceased Nobel professors			0.955*	0.417*		
			(2.07)	(2.04)		
Proximity to living Nobel professors			0.208	0.0820		
			(0.50)	(0.48)		
Proximity to earlier enNobeled professors					0.955*	0.417*
					(2.07)	(2.04)
Proximity to recently enNobeled professors					0.208	0.0820
					(0.50)	(0.48)
Year fixed effect	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
Individual fixed effects	No	No	No	No	No	No
Observations	4508	4508	4508	4508	4508	4508

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

Table 3—Probability of winning the Nobel Prize for alternative measures of distance.

	$p = -0.5$		$p = -1$		$p = -2$		$p = -1$	
	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
female	-1.099	-0.439	-1.032	-0.411	-0.953	-0.375	-0.982	-0.380
	(-1.53)	(-1.65)	(-1.43)	(-1.54)	(-1.32)	(-1.41)	(-1.36)	(-1.43)
Proximity to Nobel professors	0.234	0.101	0.598	0.243	0.568	0.228	0.236	0.0959
	(0.41)	(0.42)	(1.45)	(1.40)	(1.70)	(1.64)	(0.53)	(0.52)
Proximity to Nobel students	1.822	0.958	3.713***	1.885***	3.869***	1.852***	3.755***	1.890***
	(1.09)	(1.14)	(3.54)	(3.76)	(5.94)	(5.55)	(3.60)	(3.77)
Proximity to Nobel siblings							1.131*	0.500*
							(2.48)	(2.54)
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
Individual fixed effects	No	No	No	No	No	No	No	No
Observations	4508	4508	4508	4508	4508	4508	4508	4508

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 4—PROBABILITY OF WINNING THE NOBEL PRIZE FOR ALTERNATIVE SETS OF CANDIDATES.

	all		without ad hoc		without IDEAS/RePEc		Nobelists only	
	Logit	Probit	Logit	Probit	Logit	Probit	Logit	Probit
Female	-1.032	-0.411	-0.777	-0.318	-0.813	-0.336	8.228	3.252
	(-1.43)	(-1.54)	(-1.08)	(-1.15)	(-1.13)	(-1.21)	(1.82)	(1.92)
Proximity to Nobel professors	0.598	0.243	0.529	0.218	0.617	0.254	2.671*	1.253*
	(1.45)	(1.40)	(1.29)	(1.25)	(1.52)	(1.46)	(2.16)	(2.20)
Proximity to Nobel students	3.713***	1.885***	3.511***	1.803***	3.506***	1.793***	10.94**	5.027**
	(3.54)	(3.76)	(3.35)	(3.57)	(3.36)	(3.55)	(2.60)	(3.17)
Year fixed effect	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
Individual fixed effects	No	No	No	No	No	No	Yes	Yes
Observations	4508	4508	4091	4091	3989	3989	1827	1827

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

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Table 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	-
36	John Nash	1928	2015	1994	Princeton	C	-
37	Reinhard Selten	1930	2016	1994	Frankfurt	C	-
38	Robert Lucas	1937		1995	Chicago	E	-
39	William Vickrey	1914	1996	1996	Columbia	D	-

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ID	name	birth	death	won	alma mater	JEL	source
40	James Mirrlees	1936	2018	1996	Cambridge	D	-
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	-
71	Alvin Roth	1951		2012	Stanford	D	-
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	-

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ID	name	birth	death	won	alma mater	JEL	source
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	-
90	Ludwig von Mises	1881	1973		Vienna	P	Clarivate
91	Frank Knight	1882	1972		Cornell	D	Clarivate
92	Alvin Hansen	1887	1975		Wisconsin	E	ad hoc
93	Harold Hotelling	1895	1973		Princeton	C	Clarivate
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	Clarivate
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
100	William Baumol	1922	2017		LSE		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
104	Henri Theil	1924	2000		Utrecht	C	ad hoc
105	Harold Demsetz	1930	2019		Northwestern	K	Clarivate
106	Israel Kirzner	1930			New York	L	Clarivate
107	Wayne Fuller	1931			Iowa	C	Clarivate
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
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
117	Sam Peltzman	1940			Chicago	H	Clarivate
118	Stewart Myers	1940			Stanford	G	Clarivate
119	Guillermo Calvo	1941			Yale	E	ad hoc

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ID	name	birth	death	won	alma mater	JEL	source
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
151	Douglas Diamond	1953			Yale	G	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

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ID	name	birth	death	won	alma mater	JEL	source
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
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
175	Jordi Gali	1961			MIT	E	Clarivate
176	Andrei Shleifer	1961			MIT	G	IDEAS/RePEc
177	Stephen Bond	1963			Oxford	C	Clarivate
178	Raghuram Rajan	1963			MIT	E	Clarivate
179	Matthew Rabin	1963			MIT	D	Clarivate
180	Daron Acemoglu	1967			LSE	O	IDEAS/RePEc
181	Marc Melitz	1968			Michigan	F	Clarivate
182	John List	1968			Wyoming	D	Clarivate