

Access to Opportunity in the Sciences: Evidence from the Nobel Laureates*

Paul Novosad,¹ Sam Asher,² Catriona Farquharson,³ Eni Iljazi⁴

¹Dartmouth College

²Imperial College London

³Harvard University

⁴UPenn Wharton

May 2026

Abstract

We study the socioeconomic origins of Nobel laureates in the sciences from 1901–2023, proxied by father occupations. The average laureate grew up in a household at the 87th income and 89th education percentile in their country, and at the 94th percentile globally. Within-country ranks fell over the sample period, suggesting broader access to opportunity in the sciences. Global ranks declined only marginally. U.S.-raised laureates came from more humble backgrounds than those raised elsewhere and female laureates had more educated fathers. Laureates whose fathers were academics, engineers, or physicians disproportionately win prizes in their fathers' fields.

*This project was funded by Fast Grants for Innovations in STEM Talent Identification and Development. This paper benefited from excellent research assistance from Benjamin Levesque and Charlie Rudge. We are grateful for very helpful discussions with Kipp Bradford, James Feyrer, Matthew Gentzkow, Benny Goldman, Sasha Gusev, Ryan Hill, Adam Looney, Emir Kamenica, Douglas Staiger, Bruce Sacerdote, and Heidi Williams.

“I am, somehow, less interested in the weight and convolutions of Einstein’s brain than in the near certainty that people of equal talent have lived and died in cotton fields and sweatshops.”
— Stephen Jay Gould

1 Introduction

The question of who becomes a scientist—and whether societies make the most of their potential scientific talent—has attracted interest for over a century (Galton, 1874; Holland, 1957; Zuckerman, 1967; Merton, 1968; Berry, 1981; Morgan et al., 2022). Most quantitative work on access to scientific careers has focused on entry into the sciences or on the overall composition of researchers (Morgan et al., 2022; Stansbury and Schultz, 2023; Airoidi and Moser, 2024; Abramitzky et al., 2024; Stansbury and Rodriguez, 2024). But the social origins of those who reach the very top of the scientific hierarchy—and the frontier of discovery—are less studied.

In this paper, we propose a parsimonious quantitative measure of access to opportunity in the sciences: the average childhood socioeconomic status (SES) rank of the Nobel laureates in physiology, chemistry, physics, and economics. The laureates are scientists who reached the highest levels of their respective disciplines and produced discoveries of substantial benefit to humankind. In a world where access to opportunity is equal and outlier talent is randomly assigned, the average laureate would have an SES rank of 50. By contrast, in a world where scientific careers are accessible only to children of the top 1%, regardless of their share of top talent, the average laureate childhood SES rank would be above 99. Once we think about this spectrum, it is natural to wonder where our world falls within it.

We proxy childhood socioeconomic status of the Nobel laureates by collecting historical data on their fathers’ occupations and assigning them each a 0–100 socioeconomic rank score using U.S. Census data.¹ Occupational measures like these are widely used in historical studies on upward mobility when long panel data on individuals are unavailable (Duncan, 1966; Björklund and Jäntti, 1997; Long and Ferrie, 2013; Olivetti and Paserman, 2015; Song et al., 2020).

¹We created separate ranks based on the father’s income and the father’s education (both predicted from occupation), and we analyze each separately. Predicting SES from mothers’ occupations is less useful, due to low female labor force participation in our study period.

Our measure lets us answer two core questions. First, what is the average childhood socioeconomic rank of the Nobel laureates? Second, how has this rank changed over the 123 years since the first Nobel Prize was awarded? The answers shed light on how access to opportunity has changed in the long run—and whether human societies and institutions have become better at harnessing scientific talent from across the socioeconomic distribution in the last century.

We show that Nobel laureates predominantly grow up in families in the right tail of the income distribution, and even more so in the right tail of the education distribution. The average laureate has a father at the 87th income percentile and the 89th education percentile in their birth country. About 50–60% of laureates are from top 5% families. The most common father occupations of laureates, in order, are business owners, physicians, professors, and engineers.

Laureate families are even more elite if we adjust for income differences across countries. To do this, we create a synthetic global income distribution that takes into account father occupational earnings and national GDP per capita. The average laureate is at the 94th global income percentile.

There are clear changes over time in the national ranks. The earliest laureates grew up in families at the 91st income percentile and the 94th education percentile. The most recent laureates in our sample are from families at the 84th income percentile and the 86th education percentile. The share of laureates from the bottom 80% in their own countries more than doubled over this time.

Changes in the global income ranks were in the same direction, but smaller in magnitude. The mean global rank fell from 96 to 94 and the share of laureates from the global bottom 80% rose by a factor of 1.74; these changes are not statistically significant.²

Examining the occupations themselves, we show that between 1850 and 1950, the share of Nobel Prizes going to children of technical professionals and managers fell from 84% to 74%, a period where those occupations more than doubled in population share. The lowest-ranked occupation groups in the sample remain almost totally unrepresented—a quarter of working fathers of the post-1950 cohorts were low-skill laborers, but their children won less than 1% of prizes.

²Since the Nobel Prize is a late-career prize, our sample covers birth years 1835–1974. Our analysis therefore does not describe opportunities for present-day individuals who are still early in their scientific careers. Cohorts from the 1950s forward have incomplete coverage since some of their members will become laureates in the future. To avoid bias from incomplete coverage, our primary analysis measures time in prize years rather than birth cohorts.

Female laureates came from more educationally elite families (94th percentile on average, compared with 89th for men), suggesting that some of the barriers to advancement in the sciences faced by women could be mitigated by family investments. Women's national income ranks are also higher, but not statistically different from men's; in global income ranks, there are no gender differences.

Laureates from the U.S. came from lower SES ranks, suggesting broader access to scientific careers in the United States than in the rest of the world. This is consistent with historical evidence of high intergenerational mobility among the broader U.S. population before 1940 (Long and Ferrie, 2013; Jácome et al., 2025), the era when 75% of laureates were born. There are no significant differences in average ranks across scientific fields.

Father occupations predict laureates' Nobel disciplines. When a laureate's father works in a field that is closely tied to one of the prize disciplines (chemistry, physics, physiology, or economics), the laureate is 1.3 times more likely to win in that domain. The pattern is only slightly stronger for children of professors than it is for professionals in fields with close ties to science, such as doctors and engineers.³

Our study makes two primary contributions. First, we develop a parsimonious quantitative measure for summarizing and examining changes in access to scientific opportunity over time: the childhood SES rank of top scientific achievers. We focus on the most elite scientists making breakthrough discoveries, for whom misallocation could be most socially consequential (Romer, 1990; Aghion and Howitt, 1992; Galor and Tsiddon, 1997; Griffith et al., 2004; Akcigit et al., 2017). Second, we develop a long time series and provide new evidence that access to scientific opportunity has expanded substantially from the 19th century to the post-war era.

The study of parental occupations of scientists goes back as far as Galton (1874) and has been of perennial interest. Prior work has shown that scientists' parents are disproportionately likely to have PhDs, white collar jobs, or work as educators or in the sciences (Zuckerman, 1967; Berry,

³Classifying the extent of occupation/field overlap is subjective, but results are robust to small changes and to restricting to the children of professors whose field is easily assigned. Most father occupations have no direct relationship with any field and were excluded from this analysis.

1981; Akcigit et al., 2017; Morgan et al., 2022).⁴

In related work, Stansbury and Rodriguez (2024) study current relationships between career success in academia (and specifically in economics in Stansbury and Schultz (2023)) and parental education, finding a substantial class gap, but do not examine changes over time. Several papers study racial and gender gaps in academic advancement and recognition (Ginther et al., 2011, 2018; Sarsons et al., 2021; Hengel, 2022; Ross et al., 2022; Koffi et al., 2024).

There is a long literature on intergenerational mobility, which has most often focused on measuring average outcomes for children born into poor families (Solon, 1992; Clark and Del Bono, 2016; Chetty et al., 2014; Zimmerman, 2019; Jia and Li, 2021). Access to opportunity in the sciences is particularly important because of the high social value of scientific discovery: identifying and attracting more talented people into the sciences could affect the direction and quantity of research itself (Murphy et al., 1991; Hsieh et al., 2019; Hoogendoorn et al., 2013; Freeman and Huang, 2015; Hunt and Gauthier-Loiselle, 2010; Gaulé and Piacentini, 2013; Koning et al., 2021).

Several other studies provide useful benchmarks for our findings. In concurrent work, Abramitzky et al. (2024) estimate that U.S. academics at U.S. universities in 1900–69 had an average father SES rank of 72. Airolidi and Moser (2024) report the median U.S. scientist in 1921 had a 78th percentile father, with the median “star” scientist (rated among the 15% most successful by their peers) ranking slightly higher. At the 89th percentile, the average Nobel laureate is more elite than these broader groups. Laureates are also from more elite families than inventors; Akcigit et al. (2017) and Bell et al. (2019) show mean U.S. patent-holder ranks in the 60s and 70s, with little SES gradient in patent importance.⁵ Relative to prior work on scientists, to our knowledge ours is the first to measure how their socioeconomic representation has changed from the late 1800s to the

⁴Zuckerman (1977) notably reports father occupations of the 105 U.S.-resident pre-1972 laureates, similarly finding excess representation of business owners and other high-income careers. There is also work studying the career paths of scientists (Holland, 1957; Hargittai, 2002; Azoulay et al., 2017). Top scientists have on average attended elite colleges and graduate programs, but these are joint signals of privilege and high early ability, which are difficult to disentangle. Focusing on the laureates’ childhoods isolates a measure of privilege that they were born with. Agarwal et al. (2023) show that Math Olympiad winners from poorer countries are less likely to have research careers.

⁵Akcigit et al. (2017) report an average parent wage rank of 67 for the average U.S.-born patent holder from the 1940s birth cohort (their Figure 21). Bell et al. (2019) find average parent household earnings rank of 73 among people in the 1980–84 birth cohorts with an invention by 2014, and 74 among the same cohort with a patent in the top 5% of patent citations by 2014 (their Figure 1B).

present; even in the mobility literature, it is rare to find a 123-year time series with a comparable measure of success or childhood SES over time in a socially important domain.⁶

Our work also relates to a broader literature connecting childhood and early career circumstances to scientific achievement. Bell et al. (2019) and Aghion et al. (2017) study the childhood socioeconomic ranks of U.S. and Finnish inventors, respectively, in a similar quantitative framework to ours, while Kim and Moser (2021) examine the role of motherhood in scientific careers. A related literature studies the networked relationships between scientists who receive major prizes (Ma and Uzzi, 2018; Jin et al., 2021).

2 Biographical Data and Measurement of Socioeconomic Rank

We collected biographical information on the Nobel laureates from 1901–2023 from a range of historical sources, covering 739 winners in chemistry, physics, physiology, and economics.⁷ We exclude the prizes for Peace and for Literature, as accomplishments in these domains are more subjective and can be intentionally awarded to individuals who faced challenging childhood circumstances.

For each winner, we collected demographic information and parents’ occupations.⁸ We supplemented the data by contacting living winners directly to request information about their parents. In total, we were able to identify fathers’ occupations for 714 out of the 739 laureates, but mothers for only 181; our analysis therefore focuses on father occupation as a measure of childhood socioeconomic status.⁹

Using father occupation as a measure of childhood socioeconomic status is a common approach in the historical intergenerational mobility literature (Long and Ferrie, 2013; Song et al., 2020;

⁶On intergenerational mobility, see Solon (1992) and Chetty et al. (2014). Studies of long-run changes in intergenerational mobility are uncommon due to data limitations, and often use creative methods like classifying SES based on individuals’ names (Olivetti and Paserman, 2015; Song et al., 2020; Chetty et al., 2017).

⁷The economics prize has been awarded only since 1969; results are unchanged if the field is excluded.

⁸We collected biographical information on laureates from biographies and interviews on the official website of the Nobel Prize, other interviews with laureates, encyclopedia entries, profiles published by winners’ academic institutions, and various other biographical sources.

⁹Mother’s occupation is also less predictive of socioeconomic status than fathers, as many educated women were out of the labor force, especially in the earliest years of our sample.

Long and Ferrie, 2007). Father occupation is a good predictor of other measures of socioeconomic status, and is often the only such variable available in historical sources. We use IPUMS data from the 1850–1970 U.S. population censuses to calculate occupational earnings and education levels covering the birth years of the majority of winners. For the 12 winners born before 1850, we used occupational data from 1850. Years of education and income are recorded in the population census beginning in 1950 and 1940 respectively; we use 1940 measures for all earlier periods.¹⁰ We mapped fathers’ occupations to the 269 unique occupational categories classified in the 1950 census; where there was ambiguity over occupation classification, we tested robustness to alternate coding approaches.¹¹

We calculated the mean total individual income and education ranks for working-age men in each occupation category in each decade, and assigned these ranks to laureates’ birth decades and fathers’ occupations.¹² These ranks reflect the average income or education rank that would have been held by an adult male in the given occupation in the birth year of the laureate. Income and educational ranks are highly but imperfectly correlated; some example outliers are members of the clergy and (to a lesser extent) teachers (high education but low income ranks), and tradesmen (high income but low education ranks).

Some occupations have wide income distributions in the data; for instance, in 1850, farmers represented 65% of the American workforce. Most were relatively poor, but some were very rich. The same is true for business owners: the biographical data tells us a father is a business owner, but is often imprecise about the scale of the business. Since we have less certainty about the ranks of fathers in these groups, we run robustness analyses that exclude or use additional biographical information to rank them.

Occupational rank data are not available for all countries in which laureates were born, so our estimates are based on the U.S. occupational rank distribution. We adjusted for the different

¹⁰The census recorded information on literacy from 1850–1930, but we elected not to use these data, given their substantial inaccuracies (see, for example, Collins and Margo (2006)).

¹¹Appendix B.2 describes additional details on the calculation of occupational earnings and education levels.

¹²While the earnings and education levels associated with each occupation are held constant for all years before 1940, the ranks change over time because of changes in the distribution of occupations in the country.

occupational distributions in less-developed countries by matching country-decade pairs to the U.S. decade with the most similar level of development. For example, in 1960, a professor in India would have a higher relative socioeconomic rank in India than a professor would have in the U.S. To account for these differences, we classify the Indian professor using the U.S. rank distribution from 1850, the year in the U.S. data with the most similar per capita GDP to India in 1960 — thus assigning them a higher socioeconomic rank within their country.¹³

We describe these as *national* rank measures, as they describe the relative status of laureates' fathers within their own countries. To address income differences across countries, we use the following procedure to rank each country-decade-occupation in the global income distribution. For each country-decade pair, we create a synthetic population of individuals, reflecting the occupation distribution in the U.S. decade with the nearest per capita GDP, as above. We assign each person an occupational income equal to the 1950 U.S. census income for that occupation, multiplied by the proportional GDP difference between that country and the United States, in the given decade. We then rerank all individuals in the synthetic global population for each decade, creating a new global income rank for each country-decade-occupation group. For example, a tailor in 1950 has a U.S. occupational income rank of 55 — their position in the U.S. national income distribution. According to our global measure, a U.S. tailor in 1950 would be at the 97th percentile globally, reflecting high U.S. incomes compared with the rest of the world. Conversely, we would classify an Indian tailor in 1950 at the 46th global percentile, reflecting India's relative poverty in 1950. See Appendix B.3 for additional details and examples.

¹³The assumption that every country at a given income level has the same occupational distribution is of course imperfect, but it is an improvement over the alternative of using the U.S. distribution for all countries. The falling labor share of farmers is the largest factor in the changing occupational distribution over time, and is a near-universal fact across countries. Since there are few winners from LMICs, and high-income country occupation distributions are similar, alternate adjustments have little bearing on the findings.

3 Results

3.1 Results: Socioeconomic Ranks of Nobel Laureate Childhoods, 1901–2023

The analysis dataset consists of 714 winners from 44 countries over a period of 123 years. About 4% of winners are women, 35% grew up in the U.S., and an additional 12% in the United Kingdom.¹⁴

Figure 1 plots the distribution of the father ranks of the laureates. 68% of winners have fathers above the 90th income percentile in their birth country, 71% have fathers above the 90th education percentile, and 84% above the 90th global income percentile. In all three cases, more than half of winners are from the top 5%. The mean laureate has a father at the 87th income percentile, the 89th education percentile, and the 94th global income percentile.

Panel A of Appendix Figure A1 shows the ten most common occupations held by the fathers of laureates, along with the occupation’s census population share. Business owners, professors, physicians, and scientists feature most prominently. Relative to their occupational shares, professors are overrepresented by a factor of over 1000, physicians and engineers by 20 and 97 respectively, and business owners by a factor of 2.5.¹⁵

We next examine how the relative childhood status of laureates has changed over time. Figure 2 shows binned scatterplots of average laureate ranks, along with linear estimates of the time trend.¹⁶ Table 1 shows regression estimates of the time trend in average ranks and in indicators for families from the bottom 80% and 90%. Every 100 years, on average, there is a 6 rank point ($p < 0.01$) decline in the average national income and education ranks of laureates’ fathers. These changes are not driven by low-rank outliers; the share of laureates from the national bottom 80% and

¹⁴There are six laureates whose fathers were also Nobel laureates — one of whom (William Lawrence Bragg) shared the prize with his father (William Henry Bragg) — and one winner (Irène Joliot-Curie), whose parents were both laureates.

¹⁵The frequency distribution of father occupations is largely similar across the different prize categories (Appendix Table A1). Appendix Tables A2 and A3 show prize and census share statistics for additional occupation groups. Notably, there are no high education groups with substantial underrepresentation among the laureates, nor high income groups with substantial overrepresentation. The Online Appendix shows a similar table with a row for every occ1950 group.

¹⁶Appendix Figure A2 shows the same graphs with birth cohort on the X axis rather than prize year. We prefer prize year for the primary analysis because we do not observe the full set of laureates for birth cohorts whose members are still alive and may become laureates in the future.

90% has increased by 60–200% over the sample period, depending on the measure.¹⁷ Present-day laureates are still overwhelmingly from high-SES families, but they draw from a broader range of socioeconomic ranks than they did a century earlier.¹⁸

We can understand these trends better by looking into laureate production by occupation group. The sample period is characterized by a substantial growth of the middle class in high-income countries; the share of people in white-collar professional and managerial jobs grew from about 8% in 1850 to about 18% in 1950. If the relative advantage of parents in each occupation was fixed, we would expect to see the prize share of those occupations rise over the sample period; instead, it falls from 84% to 73% (Appendix Table A4).¹⁹ The talent pool with access to scientific opportunity is thus expanding on two margins. First, more children grow up with parents in high-opportunity professional occupations. Second, children of parents outside those occupations are gaining ground.

Disaggregating further, children of technical professionals in the 1850s cohorts received 14.6 times more prizes than their population share would predict; this relative representation ratio fell to 7.8 by the 1950s. The ratio for children of managerial professionals (where we include business owners) fell from 7.4 to only 1.7 over the same period. Farmers gained the most in relative terms. Their population share fell by a factor of four while their prize share doubled; they are still underrepresented in the 1950 birth cohort with 9% of the population and 4% of prizes. The least skilled workers (service, farm, and other laborers) remain mostly excluded; they represented over 18% of the working population in the 1950 parent cohorts, but their children received less than 1% of Nobel Prizes.

The global income distribution of laureate backgrounds has also broadened, but less so than the national rank distribution and with marginal statistical significance (Column 3 of Table 1 and Panel C of Figure 2). The average global rank has fallen by two rank points over the 123 years since 1901

¹⁷Appendix Figure A3 graphs the changes over time in the bottom-80 and bottom-90 indicator functions.

¹⁸Appendix Tables A5 and A6 show that these level and change estimates are robust to alternate approaches to occupational categories with more subjective rank classification, like aristocrats, farmers, business owners, and others, to excluding economics prizes, and to using a direct measure of education (from the historical data) rather than occupational education.

¹⁹We focus here on 1850–1950 birth cohorts since earlier and later cohorts have fewer laureates and are less precisely measured; results are similar if we use a wider sample.

($p=0.06$). The share of laureates from the global bottom 80% and bottom 90% rose by 50–80% over the sample period, but less so than the national measures and without statistical significance. The estimates suggest that there could be a substantial number of individuals with high latent scientific talent who grow up in contexts that prevent them from achieving their potential and sharing it with humanity, and that little progress has been made to close the cross-country component of this gap.²⁰

3.2 Results: Heterogeneity by Gender, Field and Region

3.2.1 Results: Inequality by Gender

Female laureates came from more educated families than male laureates, but the difference estimates are imprecise, given there have been only 28 female winners in the sciences in the 123 years of the Nobel Prize's history (Table 2, Panel A). The average female laureate has a national education rank that is 4.6 rank points higher than the average male laureate ($p=0.05$), and is more likely to be from a top-10% or top-20% education family ($p=0.13$ and $p=0.06$ respectively). The national income estimates point in the same direction but are not statistically significant.²¹ On the global income rank measures, women's ranks are very similar to men's.

The raw share of female laureates (4%) itself indicates that women have faced greater barriers to success in the sciences. Our results further suggest that high socioeconomic status can counteract some of these barriers, but it means that elite women in the sciences are drawn from an even smaller socioeconomic pool than men.

3.2.2 Results: Inequality by Field

Table 2B shows differences in the childhood socioeconomic status of Nobel laureates by prize category. The average ranks and top 10%/20% indicators are similar across fields.

²⁰Appendix Table A7 shows nearly identical results if we exclude the country GDP-based adjustment of the occupational rank distribution described in Section 2.

²¹Appendix Tables A8 and A9 show that these estimates are robust to alternate father coding choices as above. Panel B of Appendix Figure A1 shows the most common father occupations among the set of female laureates.

3.2.3 Results: Inequality by World Region

Table 2C shows the regional pattern of winners' ranks. Laureates from the U.S. tend to come from less elite backgrounds than winners from Europe and the rest of the world, suggesting more equal access to opportunity in the sciences in the United States. 39% of U.S. laureates come from the bottom 90% of their national income distributions, compared with 27% in the rest of the world, with similar differences for other measures. The regional differences are highly statistically significant. Appendix Table A10 shows regression estimates from just the United States against the rest of the world.²²

3.2.4 Heterogeneity in Time Trends

In Appendix Table A12, we examine whether the time trends vary by the subgroups examined here. The point estimates suggest some heterogeneity: access to scientific opportunity is rising the most for women; in chemistry and physiology; and in Western Europe. But these differences are imprecise and joint tests of equal trends across subgroups are for the most part not statistically significant.

3.3 Results: Father Occupation and Scientific Field

We next test whether father occupation predicts the laureate's direction of scientific research. We classified occupations to a Nobel discipline (chemistry, physics, physiology or economics) if workers in that occupation require substantive engagement with the scientific knowledge of that discipline. For professors, this was straightforward based on their field. We additionally classified doctors and surgeons to physiology, chemists and chemical engineers to chemistry, other engineers to physics, and economists to economics.

We then created a secondary classification for fields which have topical relations to the Nobel fields but do not involve a shared technical toolkit and are less directly related to academic work in the field. In this categorization, for example, we assigned actuaries and business owners to economics, veterinarians to physiology, and mechanics and repairmen to physics. Most occupations

²²Appendix Table A11 shows the list of countries by classification region.

remained unclassified as they do not have a clear link to any specific Nobel field.²³

Our aim is to test whether laureate children are more likely to be in the parent-associated field than random chance alone would predict. We use a randomization test: we take the sample of fathers whose occupations can be mapped to a Nobel field and we randomly assign their children to scientific fields based on the full sample distribution of laureate fields.²⁴ We then compare the observed own-field share with the distribution of own-field shares generated by the randomization test. Because the economics prize was only awarded in recent years, we run this test for two samples: (i) the sample of chemistry, physiology, and physics-associated parent-child pairs from 1901–2023 (N=172); and (ii) the sample including economics-associated parents since the first econ prize, 1969–2023 (N=143).

Panels A and B of Figure 3 show the distribution of parent-child field match shares from the randomization test and the empirical realization. The empirical values are in the right tails of the simulated distributions: less than 1% of the randomization values at least as large as the observed value for the non-economics sample, and 3% for the economics sample. Depending on the sample, laureates are about 25–30% more likely to receive their award in the parent-associated field than would be predicted from chance alone.

Table 3 summarizes these results, as well as results for three other samples. Splitting the sample above into professor and non-professor parents, we find that children are somewhat more likely to be in parent-associated fields when parents are professors (36–40%) than when parents are not professors (22–26%).²⁵

In short, laureates' fields are correlated with their fathers' occupations, and the correlation is stronger as the occupational knowledge base becomes closer to the academic research. This suggests

²³Appendix Table A13 shows the complete classification; many of these are subjective, but the results here are not affected by small classification changes.

²⁴We randomly assign fields based on the universe of laureate fields because the set of parents with associated fields is itself selected. For example, there are more physicists than would be expected, because engineers vastly outnumber chemists in both the census and the set of laureate parents.

²⁵For occupations with weaker and more applied relationships with the Nobel disciplines, there is at most a weak association, but this is in part because there are few occupations that could be plausibly matched to disciplines outside of economics. Appendix Figure A4 shows the simulation graphs for all of the occupation groups. Appendix Figure A5 shows the complete matrix of parent-associated fields and laureate fields for the main sample.

that parent income and education raise the probability of producing Nobel laureate children at least in part through a channel other than undifferentiated access to education or opportunity.²⁶

4 Discussion: Misallocation and Social Costs

Nobel laureates in the sciences overwhelmingly originate from the top tiers of national income and education distributions, and are even more elite in the global income distribution. This is most concerning if it implies a misallocation of talent, where people who could be making valuable scientific discoveries are instead employed in lower-value occupations, due to a lack of access career pathways in the sciences. Unfortunately, determining the extent of misallocation is difficult from the results presented here alone. In this section, we discuss several factors that influence our priors on the extent of misallocation implied by our results.

Could “missing” scientists be producing equally valuable outcomes in non-scientific domains, such as business or medical practice? There are three reasons to think their social contributions in other fields are smaller than they would be in the sciences. First, the social benefits of research in the basic sciences are plausibly among the highest out of all activities, because the externalities of research are so large (Jones and Williams, 1998; Bloom et al., 2013; Gross and Sampat, 2023). Second, talent is multidimensional; individuals with the strongest relative aptitude for science may not be equally well-matched to alternative careers (Murphy et al., 1991). Third, the unequal barriers that prevent advancement in the sciences also exist in other domains. Authors of highly cited patents are ten times more likely to come from the top 5% of the father income distribution than from the bottom 50% (Bell et al., 2019); nationality and gender play roles here as well. Results are similar for doctors, CEOs of large companies, and politicians (Dal Bó et al., 2017; Thompson et al., 2019; Bell et al., 2019). Talented individuals who face social barriers to success in the sciences are likely to find barriers in other domains as well.

²⁶This result is related to (Bell et al., 2019), who show that parent-child inventor pairs are disproportionately likely to have inventions in the same category. It is difficult to compare the ratios directly, because (Bell et al., 2019) use 445 patent categories versus our 4 field categories, finding that children are five times more likely to be in the same category as their parent than to the next nearest category.

Are “missing scientists” in fact generating important scientific discoveries, but simply not being recognized for their work? The physicist Lise Meitner was nominated for the Nobel Prize more than 40 times for her work on nuclear fission but was overlooked when the prize was given to her colleague Otto Hahn. We are doubtful that stories like this can explain a large share of our missing scientists, because gatekeeping in the sciences begins long before Nobel Prizes are being considered. To reach the top of the sciences, an individual must pass through many filters, each of which may disadvantage people from less affluent backgrounds. Entry into elite PhD programs and postdocs, grants, and early career awards are all key ingredients of success, and all of these are based on evaluation by peer scientists, like the Nobel Prize itself (Merton, 1968; Stephan, 2012). It is doubtful that the unequal outcomes we describe here are driven entirely by unequal selection only at the final stage of one’s scientific career; they more likely result from an accumulation of inequalities over the life cycle.

Could the children of elites simply be the people in their generation with the most latent scientific potential? Children born into high-income families can receive many more human capital investments than less privileged children.²⁷ To the extent that genes play a role in human capability, some amount of the correlation between parent income and child scientific output comes from heritable traits. But the extent to which genetic factors can explain the unequal distribution of laureate childhoods depends on too many unknown parameters to calibrate precisely; the nature vs. nurture debate remains unresolved.²⁸

Complementary evidence suggests unequal access to opportunity remains an important factor behind our results. The exclusionary mechanisms that have prevented access to scientific opportunity for women and minorities are widely known and were likely even larger in the era covered by our analysis; barriers facing low-income students in the sciences are well-documented. Second, the cross-country differences in scientific outputs make up a large share of the total inequality—here and in Agarwal et al. (2023)—and are not plausibly explained by genetic differences. Third, our

²⁷The investment advantage can be extreme: Irène Joliot-Curie was famously tutored by elite scientists instead of attending a conventional middle school.

²⁸Even on the most fundamental parameter to this discussion—the heritability of cognitive skills—reasonable priors remain very wide.

time series results demonstrate substantial improvement in equitable access to scientific opportunity. Past justifications of inequality based on arguments from genetics (including by Galton, the first to study the childhoods of scientists) make us cautious about accepting these arguments without clearer evidence today.²⁹

The welfare consequences of our findings also depend on the extent to which scientists are born versus made, and the extent to which scientific discoveries depend on any individual scientist. The literature is mixed on this subject. Star scientists have causal effects on scientific output (Mindruta et al., 2025; Azoulay et al., 2010), but patent/discovery races are also widespread, suggesting some substitutability (e.g. (Hill and Stein, 2025a,b)). Azoulay et al. (2019) find that deaths of eminent scientists result in *more* creative output by competitors, providing further evidence that some stars' work is substitutable and that intellectual diversity can be scientifically valuable.

Social and economic changes over the 20th century made it possible for talented people from a growing share of the socioeconomic distribution (especially in developed countries) to make it to the top of the sciences and contribute their talents to humanity. Progress at bridging global opportunity gaps has been much smaller. Our results are consistent with the existence of substantial untapped scientific talent—in lower-income countries especially—that is missing the complementary inputs for success, which could limit human progress. Improving access to those complementary inputs is desirable for the sake of fairness alone, but could also unleash new avenues of innovation, growth, and advancement for humankind.

5 Online Appendix

The online appendix contains the complete analysis dataset of Nobel laureates and their fathers' occupations, a complete set of graphs for all subgroup analyses, and detailed data on prize share for each occupation and occupation group. It can be accessed at <https://devdatalab.github.io/nobel-prizes-appendix/index.html>.

²⁹Relatedly, Bell et al. (2019) find that primary school test scores (a partial proxy for genetic talent) can explain less than a third of the SES inequality in patent authorship. Aghion et al. (2023) find that schooling improvements in Finland in the 1970s substantially lowered the causal effects of parent education on child invention, suggesting the nurture channel was important.

References

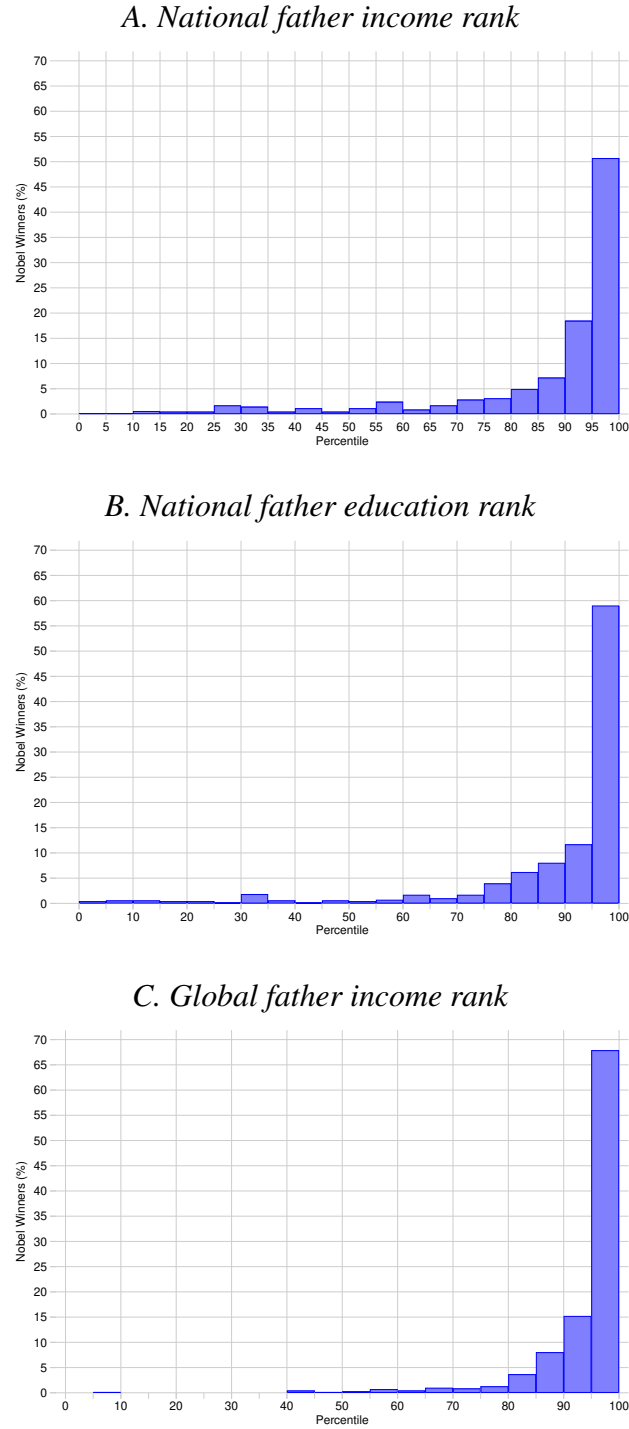
- Abramitzky, R., Greska, L., Pérez, S., Price, J., Schwarz, C., and Waldinger, F. (2024). Climbing the ivory tower: How socio-economic background shapes academia. NBER Working Paper No. 33289.
- Agarwal, R., Ganguli, I., Gaulé, P., and Smith, G. (2023). Why U.S. immigration matters for the global advancement of science. Research Policy, 52(1):104659.
- Aghion, P., Akcigit, U., Hyytinen, A., and Toivanen, O. (2017). Social Origins of Inventors. NBER Working Paper No. 24110.
- Aghion, P., Akcigit, U., Hyytinen, A., and Toivanen, O. (2023). Parental Education and Invention: The Finnish Enigma. NBER Working Paper 30964.
- Aghion, P. and Howitt, P. (1992). A Model of Growth Through Creative Destruction. Econometrica, 60(2):323–351.
- Airolidi, A. and Moser, P. (2024). Inequality in Science: Who Becomes a Star? Working Paper.
- Akcigit, U., Grigsby, J., and Nicholas, T. (2017). The Rise of American Ingenuity: Innovation and Inventors of the Golden Age. NBER Working Paper No. 29422.
- Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. American economic review, 103(5):1553–1597.
- Azoulay, P., Fons-Rosen, C., and Zivin, J. S. G. (2019). Does Science Advance One Funeral at a Time? American Economic Review, 109(8):2889–2920.
- Azoulay, P., Ganguli, I., and Zivin, J. G. (2017). The mobility of elite life scientists: Professional and personal determinants. Research policy, 46(3):573–590.
- Azoulay, P., Graff Zivin, J. S., and Wang, J. (2010). Superstar extinction. The Quarterly Journal of Economics, 125(2):549–589.
- Bell, A., Chetty, R., Jaravel, X., Petkova, N., and Van Reenen, J. (2019). Who Becomes an Inventor in America? The Importance of Exposure to Innovation. The Quarterly Journal of Economics, 134(2):647–713.
- Berry, C. (1981). The Nobel Scientists and the Origins of Scientific Achievement. The British Journal of Sociology, 32(3):381–391.
- Björklund, A. and Jäntti, M. (1997). Intergenerational Income Mobility in Sweden Compared to the United States. The American Economic Review, 87(5):1009–1018.
- Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. Econometrica, 81(4):1347–1393.
- Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., and Narang, J. (2017). The fading American dream: Trends in absolute income mobility since 1940. Science, 356(6336):398–406.

- Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States. The Quarterly Journal of Economics, 129(4):1553–1623.
- Clark, D. and Del Bono, E. (2016). The Long-Run Effects of Attending an Elite School: Evidence from the United Kingdom. American Economic Journal: Applied Economics, 8(1):150–176.
- Collins, W. J. and Margo, R. A. (2006). Historical Perspectives on Racial Differences in Schooling in the United States. In Hanushek, E. A. and Welch, F., editors, Handbook of the Economics of Education, volume 1, pages 107–154. North-Holland, Amsterdam.
- Dal Bó, E., Finan, F., Folke, O., Persson, T., and Rickne, J. (2017). Who Becomes a Politician? Quarterly Journal of Economics, 132(4):1877–1914.
- Duncan, O. D. (1966). Methodological Issues in the Analysis of Social Mobility. In Social Structure and Mobility in Economic Development. Aldine, Chicago.
- Fariss, C. J., Anders, T., Markowitz, J. N., and Barnum, M. (2022). New Estimates of Over 500 Years of Historic GDP and Population Data. Journal of Conflict Resolution, 66(3):553–591.
- Freeman, R. B. and Huang, W. (2015). Collaborating with People Like Me: Ethnic Coauthorship within the United States. Journal of Labor Economics, 33(S1):S289–S318.
- Galor, O. and Tsiddon, D. (1997). Technological Progress, Mobility, and Economic Growth. The American Economic Review, 87(3):363–382.
- Galton, F. (1874). English Men of Science: Their Nature and Nurture. Routledge.
- Gaulé, P. and Piacentini, M. (2013). Chinese Graduate Students and U.S. Scientific Productivity. The Review of Economics and Statistics, 95(2):698–701.
- Ginther, D. K., Basner, J., Jensen, U., Schnell, J., Kington, R., and Schaffer, W. T. (2018). Publications as predictors of racial and ethnic differences in NIH research awards. PLOS ONE, 13(11).
- Ginther, D. K., Schaffer, W. T., Schnell, J., Masimore, B., Liu, F., Haak, L. L., and Kington, R. (2011). Race, Ethnicity, and NIH Research Awards. Science, 333(6045):1015–1019.
- Griffith, R., Redding, S., and Reenen, J. V. (2004). Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries. The Review of Economics and Statistics, 86(4):883–895.
- Gross, D. P. and Sampat, B. N. (2023). America, Jump-Started: World War II R&D and the Takeoff of the US Innovation System. American Economic Review, 113(12):3323–3356.
- Hargittai, I. (2002). The Road to Stockholm: Nobel Prizes, Science, and Scientists. Chemical Heritage Foundation.
- Hengel, E. (2022). Publishing While Female: Are Women Held to Higher Standards? Evidence from Peer Review. The Economic Journal, 132(648):2951–2991.

- Hill, R. and Stein, C. (2025a). Race to the bottom: Competition and quality in science. The Quarterly Journal of Economics, 140(2):1111–1185.
- Hill, R. and Stein, C. (2025b). Scooped! Estimating Rewards for Priority in Science. Journal of Political Economy, 133(3).
- Holland, J. L. (1957). Undergraduate Origins of American Scientists. Science, 126(3271):433–437.
- Hoogendoorn, S., Oosterbeek, H., and van Praag, M. (2013). The Impact of Gender Diversity on the Performance of Business Teams: Evidence from a Field Experiment. Management Science, 59(7):1514–1528.
- Hsieh, C.-T., Hurst, E., Jones, C. I., and Klenow, P. J. (2019). The Allocation of Talent and U.S. Economic Growth. Econometrica, 87(5):1439–1474.
- Hunt, J. and Gauthier-Loiselle, M. (2010). How Much Does Immigration Boost Innovation? American Economic Journal: Macroeconomics, 2(2):31–56.
- Jácome, E., Kuziemko, I., and Naidu, S. (2025). Mobility for all: Representative intergenerational mobility estimates over the twentieth century. Journal of Political Economy, 133(1).
- Jia, R. and Li, H. (2021). Just Above the Exam Cutoff Score: Elite College Admission and Wages in China. Journal of Public Economics, 196(C).
- Jin, C., Ma, Y., and Uzzi, B. (2021). Scientific prizes and the extraordinary growth of scientific topics. Nature Communications, 12(1):5619.
- Jones, C. I. and Williams, J. C. (1998). Measuring the Social Return to R&D. The Quarterly Journal of Economics, 113(4):1119–1135.
- Kim, S. D. and Moser, P. (2021). Women in Science. Lessons from the Baby Boom. Working Paper NBER Working Paper No. 29436, National Bureau of Economic Research.
- Koffi, M., Pongou, R., and Wantchekon, L. (2024). Racial Inequality and Publication in Economics. AEA Papers and Proceedings, 114:300–304.
- Koning, R., Samila, S., and Ferguson, J.-P. (2021). Who do we invent for? Patents by women focus more on women’s health, but few women get to invent. Science, 372(6548):1345–1348.
- Long, J. and Ferrie, J. (2007). The Path to Convergence: Intergenerational Occupational Mobility in Britain and the US in Three Eras. The Economic Journal, 117(519).
- Long, J. and Ferrie, J. (2013). Intergenerational Occupational Mobility in Great Britain and the United States since 1850. American Economic Review, 103(4):1109–1137.
- Ma, Y. and Uzzi, B. (2018). Scientific prize network predicts who pushes the boundaries of science. Proceedings of the National Academy of Sciences, 115(50):12608–12615.
- Merton, R. K. (1968). The Matthew Effect in Science. Science, 159(3810).

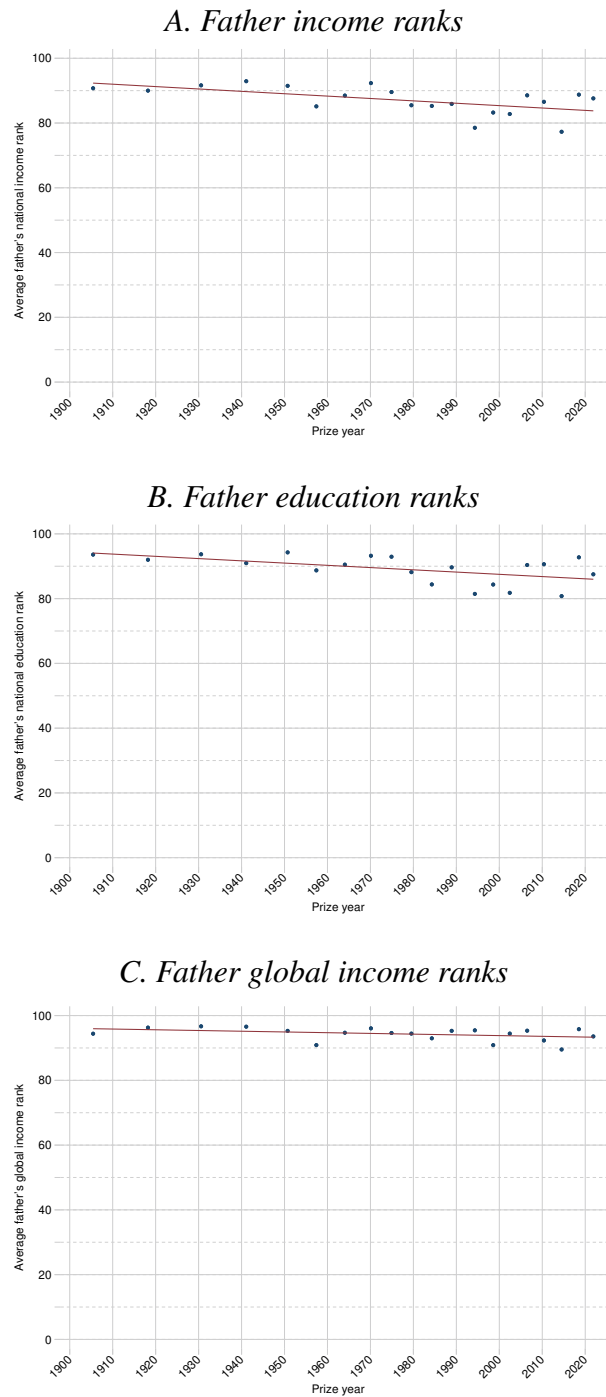
- Mindruta, D., Bercovitz, J., Mares, V., and Feldman, M. (2025). Stars in their constellations: Great person or great team? Management Science, 71(3):2170–2191.
- Morgan, A. C., LaBerge, N., Larremore, D. B., Galesic, M., Brand, J. E., and Clauset, A. (2022). Socioeconomic roots of academic faculty. Nature Human Behaviour, 6(12):1625–1633.
- Murphy, K. M., Shleifer, A., and Vishny, R. W. (1991). The Allocation of Talent: Implications for Growth. The Quarterly Journal of Economics, 106(2):503–530.
- Olivetti, C. and Paserman, M. D. (2015). In the Name of the Son (and the Daughter): Intergenerational Mobility in the United States, 1850-1940. American Economic Review, 105(8):2695–2724.
- Romer, P. M. (1990). Endogenous Technological Change. Journal of Political Economy, 98(5, Part 2):S71–S102.
- Ross, M. B., Glennon, B. M., Murciano-Goroff, R., Berkes, E. G., Weinberg, B. A., and Lane, J. I. (2022). Women are credited less in science than men. Nature, 608(7921):135–145.
- Sarsons, H., Gërxhani, K., Reuben, E., and Schram, A. (2021). Gender Differences in Recognition for Group Work. Journal of Political Economy, 129(1):101–147.
- Solon, G. (1992). Intergenerational Income Mobility in the United States. The American Economic Review, 82(3):393–408.
- Song, X., Massey, C. G., Rolf, K. A., Ferrie, J. P., Rothbaum, J. L., and Xie, Y. (2020). Long-term decline in intergenerational mobility in the United States since the 1850s. Proceedings of the National Academy of Sciences, 117(1):251–258.
- Stansbury, A. and Rodriguez, K. (2024). The Class Gap in Career Progression: Evidence from US academia. Technical report. Working Paper.
- Stansbury, A. and Schultz, R. (2023). The economics profession’s socioeconomic diversity problem. Journal of Economic Perspectives, 37(4):207–230.
- Stephan, P. (2012). How economics shapes science. Harvard University Press.
- Thompson, D. M., Feigenbaum, J. J., Hall, A. B., and Yoder, J. (2019). Who becomes a member of Congress? Evidence from de-anonymized census data. NBER Working Paper No. 26156.
- Zimmerman, S. D. (2019). Elite Colleges and Upward Mobility to Top Jobs and Top Incomes. American Economic Review, 109(1):1–47.
- Zuckerman, H. (1967). Nobel Laureates in Science: Patterns of Productivity, Collaboration, and Authorship. American Sociological Review, 32(3):391–403.
- Zuckerman, H. (1977). Scientific Elite: Nobel Laureates in the United States. The Free Press, New York.

Figure 1: Distribution of Socioeconomic Ranks of Fathers of Nobel Laureates



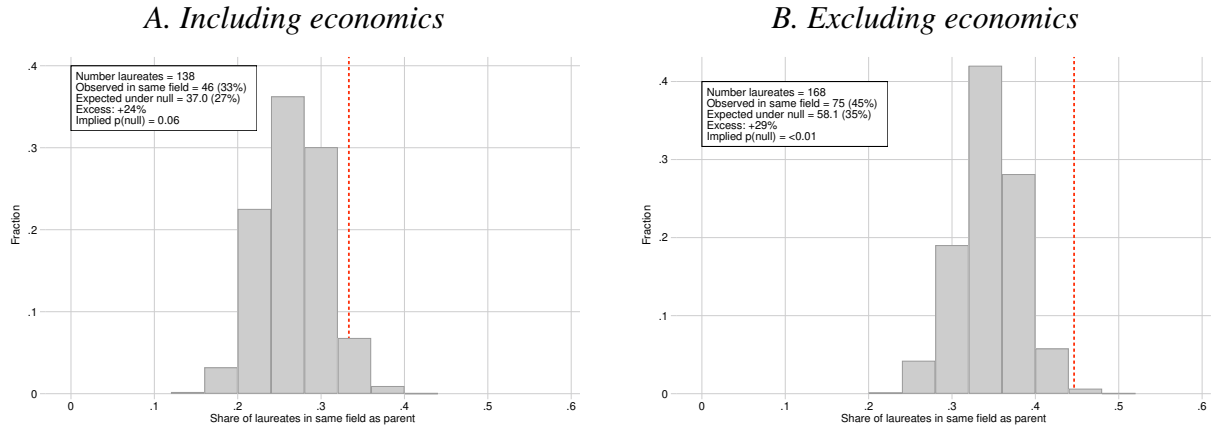
Notes: The graph shows the frequency distribution of father socioeconomic rank for all Nobel laureates in the sciences in our sample. Father income and education percentiles were predicted from father occupations, using data from the 1940 and 1950 U.S. Population Censuses. The global rank modifies the occupational income rank to account for cross-country income differences.

Figure 2: Average Socioeconomic Ranks of Fathers of Nobel Laureates



Notes: The graph shows binned scatterplots of national father's income and education rankings, and global income rankings for Nobel laureates in the sciences from 1901–2023. Father income and education percentiles were predicted from father occupations, using data from the 1940 and 1950 U.S. Population Censuses. The fitted lines are estimated using ordinary least squares (OLS).

Figure 3: Parent-Child Field Match Randomization Tests



Notes: The histograms show results from Monte Carlo simulations of the share of laureates who are in the field predicted by their parent's occupation. The red dashed lines mark the shares observed in the data. The simulations assume parent field has no effect on laureate field choice. The economics-inclusive sample includes prizes from 1969 onward; the non-economics sample uses all prizes since 1901. The sample of laureates and parents includes all laureates whose parents were professors in a field that can be matched to a Nobel field or worked with an occupation with direct ties to research in a Nobel field. Each panel uses 10,000 simulation draws. Appendix Table A13 shows the occupation-field correspondence. Appendix Figure A4 shows similar tests with different criteria for matching occupations to Nobel fields.

Table 1: Secular Trends in Socioeconomic Ranks of Fathers of Nobel Laureates

	National Income	National Education	Global Income
<i>Panel A: Average Rank</i>			
Constant (Year = 1901)	92.652*** (1.505)	94.381*** (1.282)	96.047*** (0.715)
Prize Year	-0.074*** (0.020)	-0.069*** (0.018)	-0.022** (0.010)
Observations	713	713	713
<i>Panel B: Indicator (Rank < 80)</i>			
Constant (Year = 1901)	0.064** (0.031)	0.021 (0.024)	0.020 (0.019)
Prize Year	0.0016*** (0.0004)	0.0018*** (0.0004)	0.0004* (0.0003)
Observations	713	713	713
<i>Panel C: Indicator (Rank < 90)</i>			
Constant (Year = 1901)	0.163*** (0.039)	0.176*** (0.037)	0.119*** (0.033)
Prize Year	0.0019*** (0.0005)	0.0016*** (0.0005)	0.0007 (0.0004)
Observations	713	713	713

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from OLS regressions of father socioeconomic rank measures on prize year. The prize year variable has been rescaled to a start date of zero (representing 1901), so the constant can be interpreted as the fitted value for the first year of our sample. Panel A shows the average national income, national education, and global income ranks. Panels B and C show indicators for laureates with father rank below 80 and below 90, respectively, for the same three measures. Standard errors are in parentheses.

Table 2: Heterogeneity in Socioeconomic Rank of Fathers of Nobel Laureates

	Average Rank			Top 10% Indicator			Top 20% Indicator			<i>N</i>
	National income rank	National education rank	Global income rank	National income rank	National education rank	Global income rank	National income rank	National education rank	Global income rank	
Full Sample	87.13 (0.70)	89.17 (0.67)	94.36 (0.34)	0.69 (0.02)	0.71 (0.02)	0.83 (0.01)	0.81 (0.01)	0.85 (0.01)	0.95 (0.01)	713
<i>Panel A: Gender</i>										
Male	87.04 (0.72)	88.98 (0.69)	94.39 (0.34)	0.69 (0.02)	0.70 (0.02)	0.83 (0.01)	0.81 (0.01)	0.84 (0.01)	0.95 (0.01)	685
Female	89.46 (2.89)	93.60 (2.26)	93.61 (1.83)	0.75 (0.08)	0.82 (0.07)	0.79 (0.08)	0.82 (0.07)	0.93 (0.05)	0.93 (0.05)	28
F-test	[0.42]	[0.05]	[0.68]	[0.47]	[0.11]	[0.54]	[0.90]	[0.09]	[0.68]	
<i>Panel B: Prize Category</i>										
Chemistry	86.68 (1.38)	88.15 (1.32)	93.95 (0.66)	0.69 (0.03)	0.64 (0.03)	0.81 (0.03)	0.82 (0.03)	0.82 (0.03)	0.96 (0.02)	186
Physics	87.22 (1.29)	90.20 (1.23)	93.50 (0.62)	0.68 (0.03)	0.75 (0.03)	0.80 (0.03)	0.80 (0.03)	0.88 (0.02)	0.93 (0.02)	212
Physiology	87.70 (1.26)	89.30 (1.20)	95.11 (0.60)	0.72 (0.03)	0.73 (0.03)	0.86 (0.03)	0.83 (0.03)	0.85 (0.02)	0.95 (0.01)	223
Economics	86.46 (1.96)	88.51 (1.87)	95.32 (0.94)	0.64 (0.05)	0.68 (0.05)	0.87 (0.04)	0.79 (0.04)	0.82 (0.04)	0.97 (0.02)	92
F-test	[0.93]	[0.70]	[0.18]	[0.55]	[0.09]	[0.24]	[0.80]	[0.37]	[0.47]	
<i>Panel C: Regions</i>										
USA	84.14 (1.16)	86.63 (1.11)		0.62 (0.03)	0.60 (0.03)		0.74 (0.02)	0.76 (0.02)		258
Western Europe	89.00 (1.04)	90.96 (1.00)		0.72 (0.03)	0.75 (0.03)		0.85 (0.02)	0.90 (0.02)		317
Eastern Europe	92.04 (2.51)	93.40 (2.40)		0.84 (0.06)	0.89 (0.06)		0.89 (0.05)	0.95 (0.05)		55
Global South	89.28 (3.65)	90.03 (3.50)		0.73 (0.09)	0.85 (0.09)		0.88 (0.08)	0.85 (0.07)		26
All others	84.58 (2.46)	86.16 (2.36)		0.70 (0.06)	0.68 (0.06)		0.79 (0.05)	0.86 (0.05)		57
F-test	[0.00]	[0.01]		[0.01]	[0.00]		[0.01]	[0.00]		

Notes: The table shows group means for measures of Nobel laureate fathers' socioeconomic status in different subsamples. Global income is intentionally left out as it is not meaningful to compare it across regions. Standard errors are in parentheses. The Top X% indicators take the value 1 if the laureate has a father in the top X% of the given father distribution. P-values from the F-test of equality of all group means are displayed below each set of means. Appendix Table A11 lists the countries in each region.

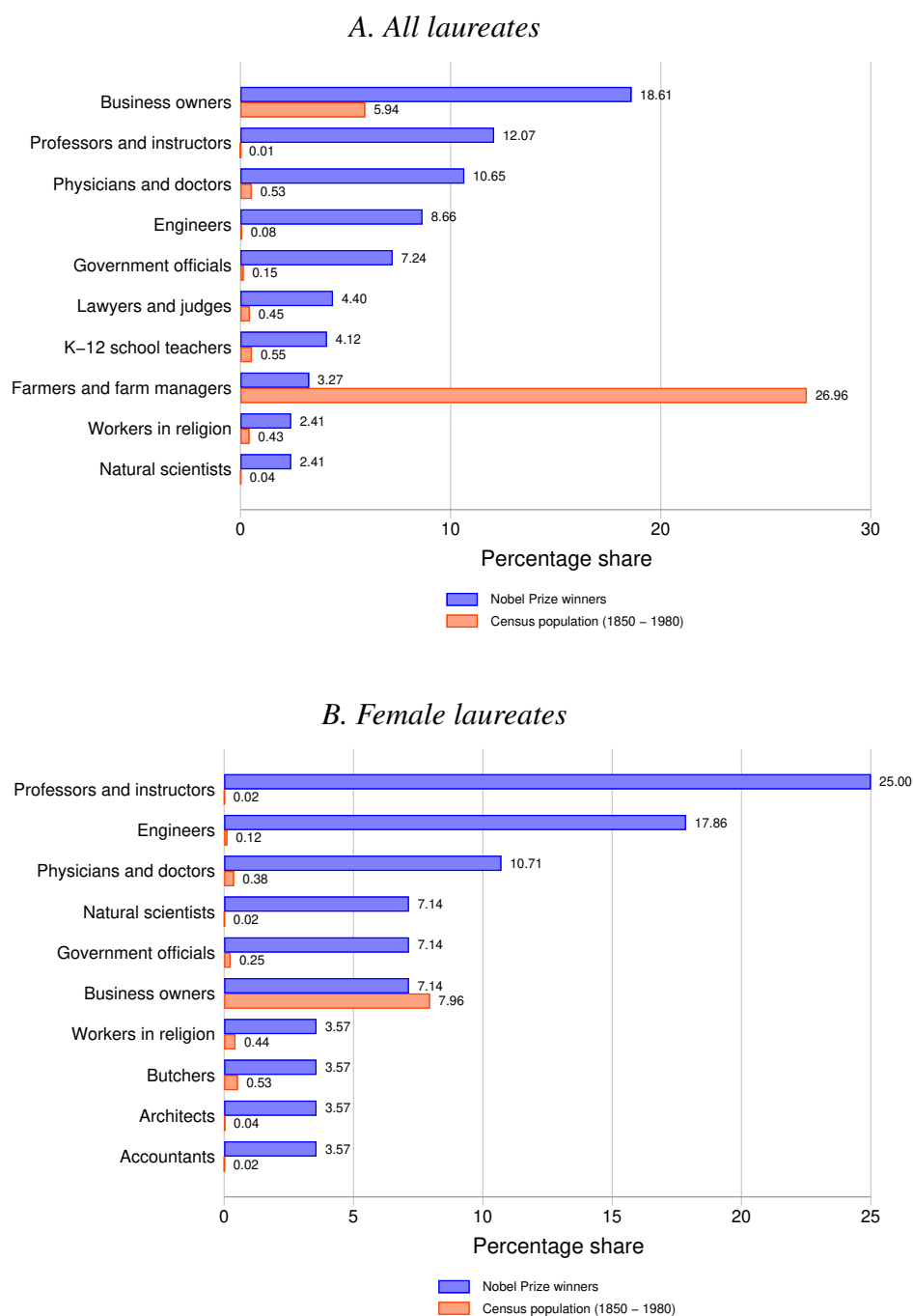
Table 3: Parent-Child Field Match Randomization Tests

	Main Sample		Professors		Technical Matches		Topical Matches	
Number laureates	168	138	50	40	118	98	17	153
Observed in same field	75 (45%)	46 (33%)	21 (42%)	13 (32%)	54 (46%)	33 (34%)	7 (41%)	36 (24%)
Expected under null	58.1 (35%)	37.0 (27%)	17.0 (34%)	10.1 (25%)	41.0 (35%)	26.9 (27%)	5.9 (34%)	31.7 (21%)
Excess	+29%	+24%	+23%	+29%	+32%	+23%	+19%	+14%
Implied p(null)	<0.01	0.06	0.09	0.11	0.01	0.07	0.37	0.22
Prizes include Economics		X		X		X		X
Years	all	≥ 1969	all	≥ 1969	all	≥ 1969	all	≥ 1969

Notes: The table reports results from Monte Carlo simulations of the share of laureates who are in the field predicted by their parent's occupation. The simulations assume parent field has no effect on laureate field choice; the table shows the comparison with the actual share of laureates observed in the same field. The economics-inclusive sample includes prizes from 1969 onward; the non-economics sample uses all prizes since 1901. The implied p(null) value is the share of simulations that resulted in a value at least as extreme as the empirical value. The main sample includes both professors and professionals who directly apply scientific knowledge from a Nobel field in their work. The second and third subsets show these two groups separately. The fourth subset uses a sample of parents in occupations with topical overlap with Nobel fields but less direct scientific overlap.

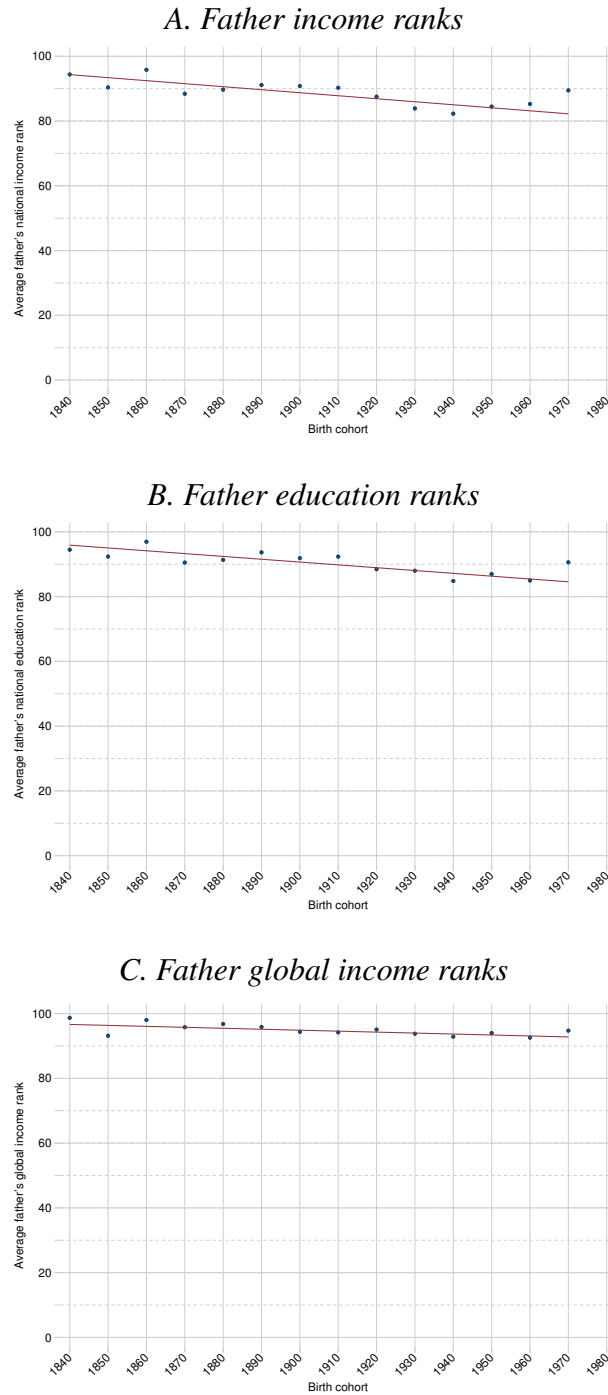
A Additional Figures and Tables

Figure A1: Most Frequent Father Occupations among Nobel Laureates



Notes: The graphs show father-occupation distributions among Nobel laureates in the sciences (in blue) and the general population (in orange). Panel A includes all laureates; Panel B restricts to female laureates. Occupational shares are averages from the U.S. Population Census between 1850 and 1970. The laureate sample covers 1901–2023.

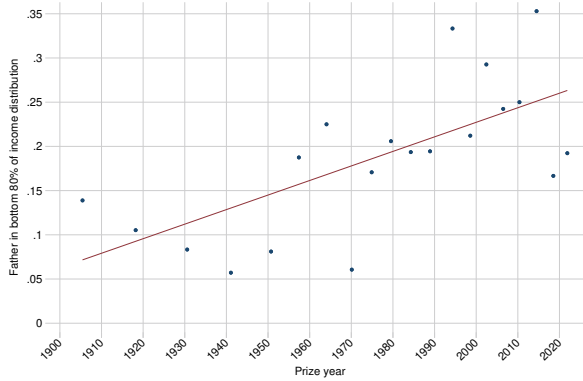
Figure A2: Average Socioeconomic Ranks of Fathers of Nobel Laureates by Birth Cohort



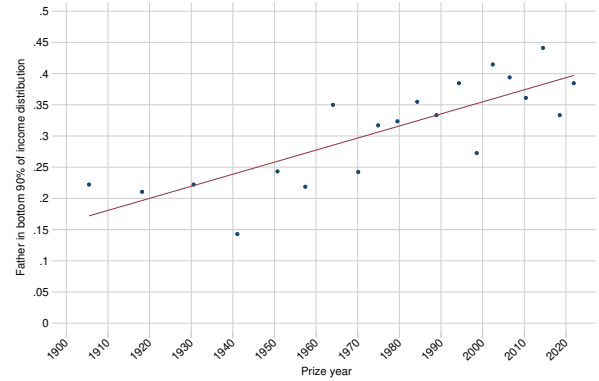
Notes: The graph shows binned scatterplots of national father's income and education rankings, and global income rankings for Nobel laureates in the sciences from 1901–2023, with birth cohort on the x-axis rather than prize year. Father income and education percentiles were predicted from father occupations, using data from the 1940 and 1950 U.S. Population Censuses. The fitted lines are estimated using ordinary least squares (OLS).

Figure A3: Share of Laureates with Non-Elite Fathers over Time

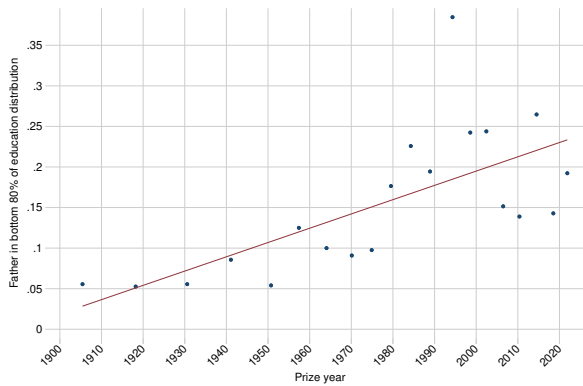
A. Father below 80th income percentile



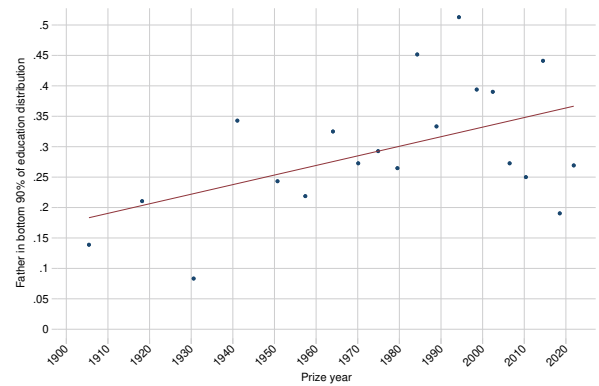
B. Father below 90th income percentile



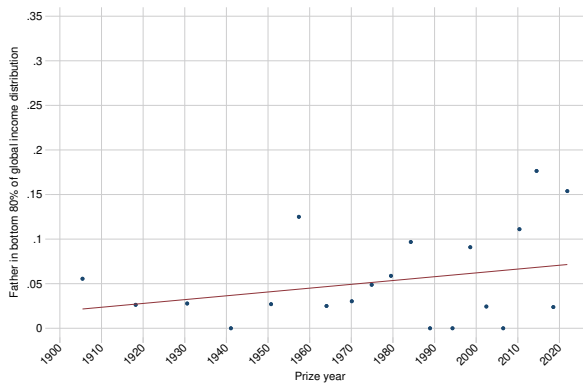
C. Father below 80th education percentile



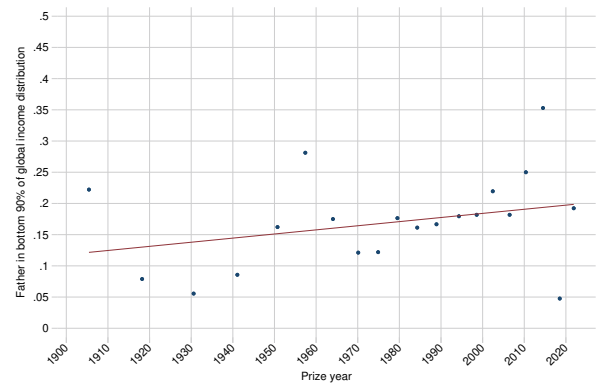
D. Father below 90th education percentile



E. Father below 80th global income percentile

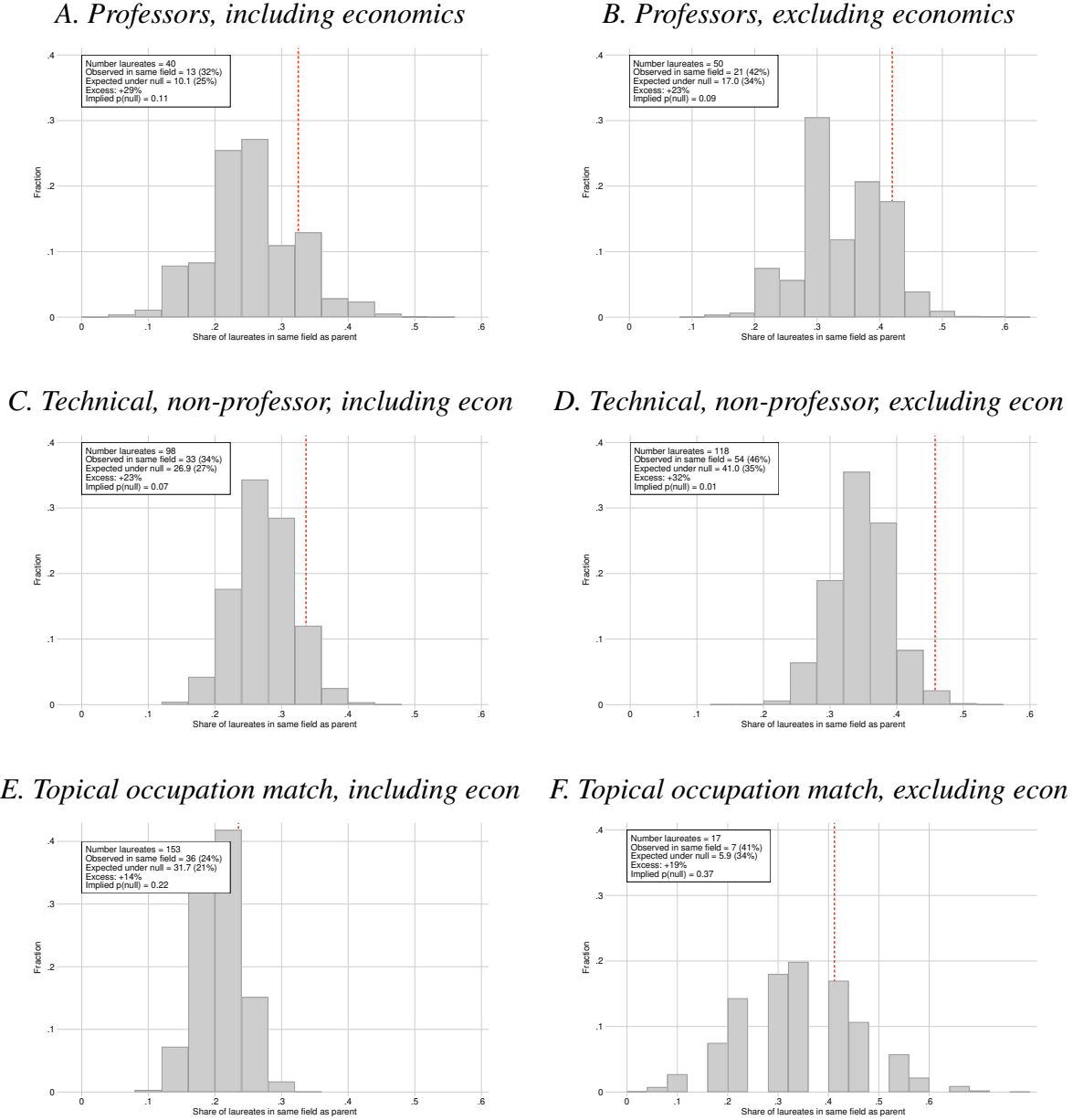


F. Father below 90th global income percentile



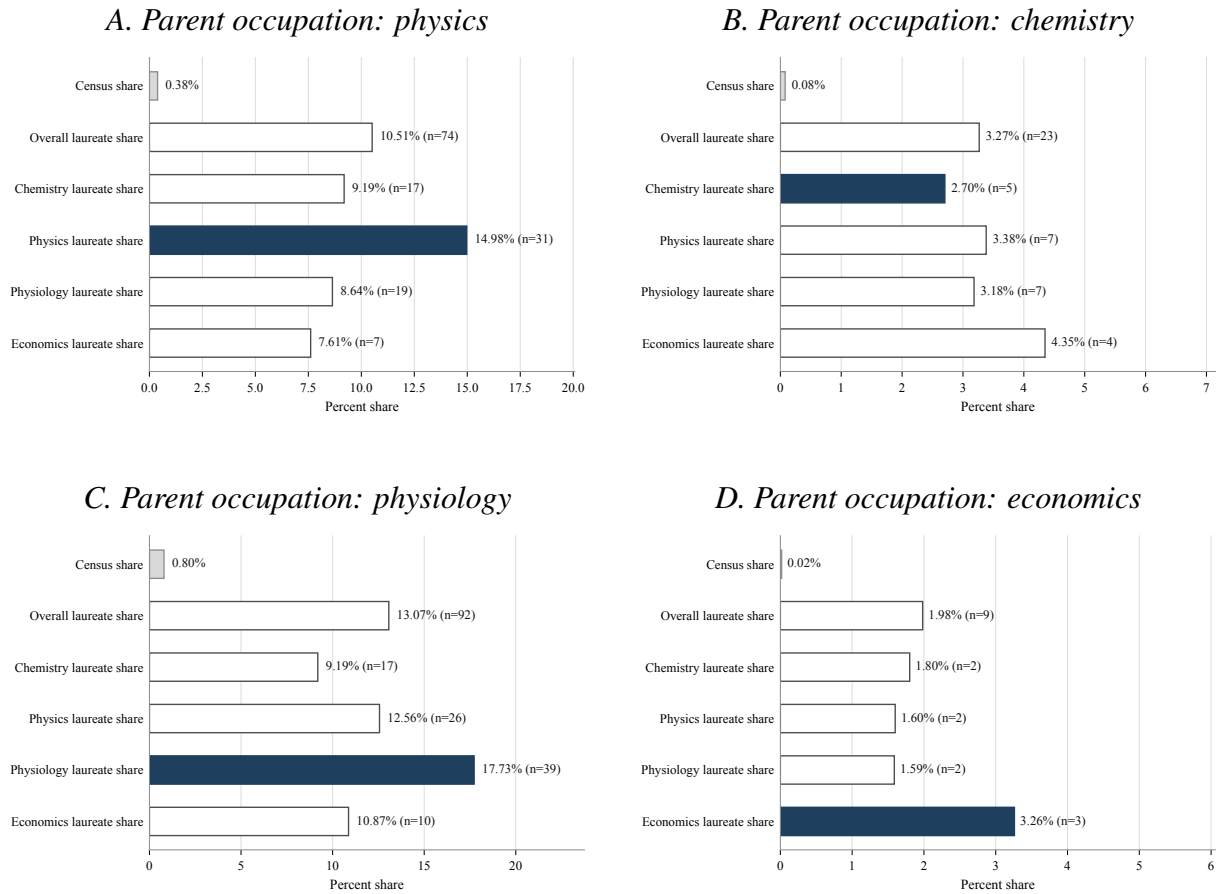
Notes: The graphs show binned scatterplots of the share of Nobel laureates whose fathers were below the 80th percentile (left column) or 90th percentile (right column) of the national income (Panels A and B), national education (Panels C and D), and global income (Panels E and F) distributions.

Figure A4: Parent-Child Field Match Randomization Tests: Professor, Nonprofessional, and Weak Matches



Notes: The histograms show results from Monte Carlo simulations of the share of laureates who are in the field predicted by their parent's occupation. The red dashed lines mark the shares observed in the data. The simulations assume parent field has no effect on laureate field choice. The economics-inclusive sample includes prizes from 1969 onward; the non-economics sample uses all prizes since 1901. Panels A and B limit the sample to professors with Nobel-matched fields. Panels C and D limit the sample to occupations that require substantive engagement with the scientific knowledge of a Nobel field. Panels E and F limit the sample to occupations with topical links but less direct scientific overlap. Each panel uses 10,000 simulation draws. Appendix Table A13 shows the occupation-field correspondence.

Figure A5: Combined Field-Matched Father Occupation Shares by Nobel Prize Field



Notes: The graphs show the distribution of laureate fields among parents who are professors in Nobel disciplines or have occupations that engage with science from Nobel disciplines. The economics panel limits the sample to prizes awarded in 1969 or later.

Table A1: Most Common Father Occupations of Nobel Laureates, by Prize Category

Father Occupation	Prize Category			
	Chemistry	Physics	Physiology	Economics
Business Owners	22%	17%	17%	20%
Physicians and doctors	8%	8%	15%	11%
Professors and academics	10%	17%	10%	9%
Engineers	8%	10%	8%	7%
Natural Scientists	2%	1%	2%	5%
Lawyers and Judges	4%	2%	5%	7%
Government Officials	6%	8%	8%	7%
Teachers	5%	6%	2%	4%
Retail Workers	3%	2%	2%	1%
Farmers	3%	3%	3%	4%
Observations	185	211	223	92

Notes: The table shows the ten most common occupations among fathers of the Nobel laureates in our sample, by prize category.

Table A2: Occupation Shares by 10-Group Category

Occupation Group	Average education rank	Average national income rank	Laureate fathers	Prize share	Census share	Over-rep. ratio
Technical professional	97.6	85.6	363	51.6%	4.3%	11.99
Managers, officials, and proprietors	85.7	92.7	191	27.1%	7.0%	3.88
Sales workers	86.3	78.2	33	4.7%	4.0%	1.16
Clerical and kindred	90.9	77.1	14	2.0%	3.2%	0.62
Craftsmen	59.8	69.2	54	7.7%	16.9%	0.45
Operatives	58.5	65.5	16	2.3%	13.5%	0.17
Service workers	60.1	47.4	3	0.4%	3.2%	0.13
Farm owners, tenants, and managers	28.3	23.9	23	3.3%	26.8%	0.12
Laborers	43.0	43.8	6	0.9%	12.9%	0.07
Farm laborers	9.5	4.6	1	0.1%	8.7%	0.02

Notes: The table shows characteristics of the sample, split into occ1950 1-digit occupation categories. The census population share is the share of working-age men with this primary occupation. The overrepresentation ratio is the laureate prize share divided by the census population share. Aristocrats and large estate holders with no specified occupation are excluded.

Table A3: Occupation Shares by 25-Group Category

Occupation Group	Average education rank	Average national income rank	Laureate fathers	Prize share	Census share	Over-rep. ratio
Professional specialty	97.8	85.5	343	48.7%	3.8%	12.98
Management-related	92.6	92.0	21	3.0%	0.5%	5.69
Financial sales and related	94.6	86.9	8	1.1%	0.3%	4.32
Exec/ admin/ managerial	86.1	92.6	184	26.1%	6.5%	4.03
Technicians and related support	94.1	79.7	4	0.6%	0.3%	2.25
Administrative support	90.8	78.0	26	3.7%	3.4%	1.07
Housekeeping/ cleaning/ laundry	56.0	43.2	2	0.3%	0.3%	1.00
Mechanics and repairers	75.3	75.0	11	1.6%	1.8%	0.86
Precision production and craft	67.3	81.4	27	3.8%	5.6%	0.68
Retail sales	85.4	77.2	14	2.0%	3.7%	0.54
Building and grounds cleaning/ maintenance	53.2	39.0	2	0.3%	0.5%	0.52
Construction trades	60.7	63.7	13	1.8%	5.8%	0.32
Machine operators/ assemblers/ inspectors	54.9	65.9	14	2.0%	10.1%	0.20
Food preparation and service	70.0	49.3	1	0.1%	0.8%	0.18
Fire fighting/ police/ corrections	80.5	40.5	1	0.1%	1.0%	0.14
Farm operators and managers	28.3	23.9	23	3.3%	26.8%	0.12
Extractive/ mining	11.2	58.6	1	0.1%	2.1%	0.07
Transportation and material moving	51.5	51.5	7	1.0%	16.3%	0.06
Other agricultural and related	9.5	5.5	2	0.3%	9.3%	0.03
Guards and guard supervisors	55.0	62.9	0	0.0%	0.3%	0.00
Health service support	78.6	47.4	0	0.0%	0.1%	0.00
Misc. personal care and services	36.8	14.1	0	0.0%	0.5%	0.00
Personal appearance	61.9	53.9	0	0.0%	0.4%	0.00
Recreation and hospitality	60.7	42.1	0	0.0%	0.4%	0.00

Notes: The table shows characteristics of the sample, split into 25 occupation categories from Autor and Dorn (2013). The census population share is the share of working-age men with this primary occupation. The overrepresentation ratio is the laureate prize share divided by the census population share. Aristocrats and large estate holders with no specified occupation are excluded.

Table A4: Changes in Relative Representation by Occupation Category

Occupation group	1850 prize share	1850 census share	1950 prize share	1950 census share	1850 relative rep.	1950 relative rep.	Change in prize share (pp)
Technical professional	43.8%	3.2%	55.2%	7.3%	13.80	7.60	11.4
Farm owners, tenants, and managers	3.2%	44.3%	3.3%	9.2%	0.07	0.36	0.2
Managers, officials, and proprietors	40.8%	5.2%	20.5%	10.4%	7.91	1.98	-20.3
Clerical and kindred	2.0%	0.3%	1.9%	6.5%	6.71	0.29	-0.1
Sales workers	2.3%	2.1%	5.9%	6.2%	1.11	0.96	3.6
Craftsmen	7.3%	18.3%	7.9%	21.3%	0.40	0.37	0.6
Operatives	-0.5%	9.1%	3.7%	20.8%	-0.06	0.18	4.2
Service workers	1.3%	1.1%	-0.2%	5.9%	1.23	-0.03	-1.5
Farm laborers	0.1%	4.5%	0.1%	4.0%	0.03	0.03	0.0
Laborers	-0.3%	12.5%	1.5%	8.6%	-0.02	0.18	1.8

Notes: The table reports the share of workers in each occupation group in 1850 and 1950, along with the share of Nobel laureate parents in that occupation group. To reduce noise, the laureate shares are predicted from linear regressions of laureate share on laureate birth year. Relative representation is the laureate share divided by the census share. The change in prize share for each occupation group is reported in percentage points. The occupation groups are 1-digit occupation groups from the occ1950 Census classification system.

Table A5: SES Ranks of Fathers of Nobel Laureates: Robustness

	National Income Rank	National Education Rank
<i>Panel A: Sample excluding difficult to classify observations</i>		
Constant (Year = 1901)	92.632 (1.533)	94.424 (1.306)
Prize Year	-0.072*** (0.020)	-0.070*** (0.018)
Observations	700	700
<i>Panel B: Sample excluding aristocrats</i>		
Constant (Year = 1901)	92.171 (1.571)	94.013 (1.340)
Prize Year	-0.068*** (0.021)	-0.066*** (0.019)
Observations	704	704
<i>Panel C: Sample excluding business owners and farmers</i>		
Constant (Year = 1901)	93.827 (1.378)	97.436 (0.983)
Prize Year	-0.072*** (0.018)	-0.067*** (0.015)
Observations	559	559
<i>Panel D: Sample excluding Economics</i>		
Constant (Year = 1901)	92.786 (1.538)	94.678 (1.309)
Prize Year	-0.077*** (0.021)	-0.075*** (0.020)
Observations	621	621

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from an OLS regression of Nobel laureate father SES rank on a linear time trend. These specifications are based on the primary specification in Table 1, with the following modifications. In Panel A, we exclude 13 laureates whose father occupations were vaguely described and difficult to classify. In Panel B, we exclude 8 laureates whose fathers were aristocrats (who were classified as being at education and income percentile 100 in the main analysis). In Panel C, we exclude 134 children of business owners and farmers, since these occupations can be associated with a wide range of possible SES ranks. In Panel D, we exclude the Nobel Prize in economics.

Table A6: SES Ranks of Fathers of Nobel Laureates: Robustness to Alternate Codings

	National Income Rank	National Education Rank
<i>Panel A: Heterogeneous coding of business owners</i>		
Constant (Year = 1901)	92.480 (1.519)	93.928 (1.330)
Prize Year	-0.076*** (0.020)	-0.073*** (0.018)
Observations	713	713
<i>Panel B: Recoding education according to biographies</i>		
Constant (Year = 1901)		94.090 (1.305)
Prize Year		-0.071*** (0.018)
Observations		713
<i>Panel C: Recoding education and heterogeneous business owners</i>		
Constant (Year = 1901)		93.845 (1.340)
Prize Year		-0.072*** (0.018)
Observations		713

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from an OLS regression of Nobel laureate father SES rank on a linear time trend. These specifications are based on the primary specification in Table 1, with the following modifications. In Panel A, we classified business owners as small, medium or large. For small business owners, we used the 25th percentile education and income data from the Census to calculate the father's rank. For large business owners, we used the 75th. In Panel B, we override the father's education rank in cases where the historical record documents the actual education level of the father. In Panel C, we do both.

Table A7: Global Rank Estimates: Robustness to National Occupation Distribution Adjustment

	Global Rank (Original)	Global Rank (No Occupation Adjustment)
Constant (Year = 1901)	96.047*** (0.715)	95.873*** (0.764)
Prize Year	-0.022** (0.010)	-0.028*** (0.011)
Observations	713	713

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from a regression of laureate global ranking on a constant and on the number of years since the first Nobel Prize in 1901. Column 1 corresponds to the primary estimates displayed in Panel C of Figure 2. In Column 2, global income ranks are calculated *without* adjusting national occupation rank distributions for country GDP level. Standard errors are in parentheses.

Table A8: Differences in Average SES Rank of Laureate Fathers, by Gender: Robustness

	Average Rank		Top 10% Indicator		Top 20% Indicator	
	National Income Rank	National Education Rank	National Income Rank	National Education Rank	National Income Rank	National Education Rank
<i>Panel A: Sample excluding difficult to classify observations</i>						
Constant	87.038 (0.730)	88.975 (0.702)	0.689 (0.018)	0.700 (0.018)	0.813 (0.015)	0.844 (0.014)
Female Winner	3.827 (2.726)	4.660 (2.445)	0.088 (0.082)	0.115 (0.077)	0.039 (0.070)	0.082 (0.052)
Observations	700	700	700	700	700	700
<i>Panel B: Sample excluding aristocrats</i>						
Constant	86.877 (0.729)	88.851 (0.701)	0.685 (0.018)	0.697 (0.018)	0.809 (0.015)	0.842 (0.014)
Female Winner	2.581 (2.976)	4.752 (2.364)	0.065 (0.084)	0.125* (0.075)	0.012 (0.074)	0.087* (0.051)
Observations	704	704	704	704	704	704
<i>Panel C: Sample excluding business owners and farmers</i>						
Constant	88.253 (0.716)	92.180 (0.671)	0.649 (0.021)	0.811 (0.017)	0.801 (0.017)	0.886 (0.014)
Female Winner	1.151 (3.189)	2.512 (2.386)	0.120 (0.085)	0.074 (0.065)	0.007 (0.079)	0.076* (0.040)
Observations	559	559	559	559	559	559
<i>Panel D: Sample excluding Economics</i>						
Constant	87.064 (0.779)	89.060 (0.745)	0.693 (0.019)	0.703 (0.019)	0.814 (0.016)	0.847 (0.015)
Female Winner	4.120 (2.930)	5.057 (2.527)	0.147* (0.076)	0.137* (0.076)	0.026 (0.075)	0.113*** (0.042)
Observations	621	621	621	621	621	621

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from an OLS regression of Nobel laureate father SES rank on an indicator for female laureates. The specifications are based on those in Panel A of Table 2, with the following modifications. In Panel A, we exclude 13 laureates whose father occupations were vaguely described and difficult to classify. In Panel B, we exclude eight laureates whose fathers were aristocrats (who were classified as being at education and income percentile 100 in the main analysis). In Panel C, we exclude 134 children of business owners and farmers, since these occupations can be associated with a wide range of possible SES ranks. In Panel D, we exclude the Nobel Prize in economics.

Table A9: Differences in Average SES Rank of Laureate Fathers, by Gender: Robustness to Alternate Codings

	Average Rank		Top 10% Indicator		Top 20% Indicator	
	National Income Rank	National Education Rank	National Income Rank	National Education Rank	National Income Rank	National Education Rank
<i>Panel A: Heterogeneous coding of business owners</i>						
Constant	86.749 (0.734)	88.339 (0.756)	0.677 (0.018)	0.707 (0.017)	0.800 (0.015)	0.836 (0.014)
Female Winner	1.254 (3.274)	2.727 (3.717)	0.037 (0.087)	0.115 (0.075)	-0.014 (0.079)	0.056 (0.060)
Observations	713	713	713	713	713	713
<i>Panel B: Recoding education according to biographies</i>						
Constant		88.656 (0.717)		0.702 (0.017)		0.841 (0.014)
Female Winner		2.383 (3.374)		0.084 (0.080)		0.016 (0.068)
Observations		713		713		713
<i>Panel C: Recoding education and heterogeneous business owners</i>						
Constant		88.311 (0.754)		0.708 (0.017)		0.835 (0.014)
Female Winner		2.727 (3.382)		0.078 (0.080)		0.022 (0.068)
Observations		713		713		713

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from an OLS regression of Nobel laureate father SES rank on an indicator for female laureates. The specifications are based on those in Panel A of Table 2, with the following modifications. In Panel A, we classified business owners as small, medium or large. For small business owners, we used the 25th percentile education and income data from the Census to calculate the father's rank. For large business owners, we used the 75th. In Panel B, we override the father's education rank in cases where the historical record documents the actual education level of the father. In Panel C, we do both.

Table A10: Father Ranks of Nobel Laureates: USA vs. Rest of World

	Average Rank		Top 10% Indicator		Top 20% Indicator	
	National Income Rank	National Education Rank	National Income Rank	National Education Rank	National Income Rank	National Education Rank
Constant	88.827 (0.827)	90.604 (0.793)	0.734 (0.021)	0.765 (0.020)	0.851 (0.017)	0.895 (0.014)
U.S. childhood	-4.686*** (1.507)	-3.974*** (1.444)	-0.118*** (0.037)	-0.164*** (0.036)	-0.106*** (0.032)	-0.131*** (0.030)
Observations	713	713	713	713	713	713

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from OLS regressions of SES ranks of fathers of Nobel laureates on an indicator that takes the value one for laureates who spent their childhood in the United States. Standard errors are reported in parentheses.

Table A11: Countries in Each Region

Western Europe	Eastern Europe	Global South	Others
Austria	Azerbaijan	Algeria	Australia
Belgium	Belarus	Argentina	Canada
Cyprus	Bosnia and Herzegovina	Brazil	Israel
Denmark	Croatia	China	Japan
Finland	Czech Republic	Egypt	New Zealand
France	Hungary	India	Turkey
Germany	Latvia	Indonesia	
Ireland	Lithuania	Lebanon	
Italy	Poland	Mexico	
Luxembourg	Romania	Morocco	
Netherlands	Russia	Pakistan	
Norway	Slovakia	South Africa	
Portugal	Slovenia	South Korea	
Spain	Ukraine	Taiwan	
Sweden		Venezuela	
Switzerland			
United Kingdom			

Notes: The table lists the countries included in each of the geographical regions used in the analysis for Table 2.

Table A12: Secular Trends in Average Father SES Rank of Nobel Laureates, by Subgroup

	Average Rank			100 * Top 10% Indicator			100 * Top 20% Indicator			N
	National income rank	National education rank	Global income rank	National income rank	National education rank	Global income rank	National income rank	National education rank	Global income rank	
Full Sample	-0.074*** (0.020)	-0.069*** (0.018)	-0.022** (0.010)	-0.193*** (0.050)	-0.157*** (0.047)	-0.066 (0.042)	-0.165*** (0.041)	-0.176*** (0.035)	-0.043* (0.026)	713
<i>Panel A: Gender</i>										
Male	-0.075*** (0.021)	-0.074*** (0.019)	-0.023** (0.010)	-0.191*** (0.051)	-0.166*** (0.048)	-0.067 (0.042)	-0.164*** (0.042)	-0.186*** (0.037)	-0.038 (0.026)	685
Female	-0.116* (0.060)	-0.082* (0.046)	-0.009 (0.054)	-0.492*** (0.180)	-0.280 (0.173)	0.047 (0.323)	-0.304** (0.140)	-0.168 (0.119)	-0.172 (0.121)	28
F-test	[0.523]	[0.878]	[0.797]	[0.108]	[0.523]	[0.727]	[0.337]	[0.887]	[0.276]	
<i>Panel B: Prize Category</i>										
Chemistry	-0.138*** (0.032)	-0.113*** (0.034)	-0.057*** (0.018)	-0.312*** (0.092)	-0.198** (0.099)	-0.195** (0.081)	-0.296*** (0.063)	-0.278*** (0.063)	-0.107*** (0.040)	186
Physics	-0.002 (0.038)	-0.011 (0.034)	-0.010 (0.017)	-0.036 (0.090)	-0.085 (0.079)	-0.043 (0.077)	-0.058 (0.079)	-0.027 (0.065)	-0.031 (0.049)	212
Physiology	-0.102*** (0.038)	-0.109*** (0.033)	-0.022 (0.018)	-0.217** (0.090)	-0.259*** (0.081)	-0.060 (0.077)	-0.179** (0.081)	-0.249*** (0.064)	-0.033 (0.056)	223
Economics	-0.056 (0.117)	0.022 (0.115)	0.022 (0.061)	-0.490 (0.321)	0.395 (0.309)	0.341 (0.258)	-0.143 (0.258)	-0.163 (0.242)	0.028 (0.140)	92
F-test	[0.055]	[0.085]	[0.200]	[0.133]	[0.124]	[0.176]	[0.130]	[0.028]	[0.504]	
<i>Panel C: Regions</i>										
USA	-0.026 (0.044)	-0.027 (0.038)		-0.104 (0.124)	0.102 (0.122)		-0.103 (0.103)	-0.155* (0.090)		258
Western Europe	-0.079*** (0.028)	-0.062** (0.026)		-0.214*** (0.069)	-0.183*** (0.065)		-0.152*** (0.056)	-0.126** (0.049)		317
Eastern Europe	0.027 (0.042)	-0.012 (0.036)		-0.121 (0.162)	-0.033 (0.155)		-0.029 (0.158)	-0.098 (0.085)		55
Global South	-0.123 (0.086)	-0.149 (0.117)		-0.304 (0.332)	-0.326 (0.209)		-0.412* (0.232)	-0.326 (0.209)		26
All others	-0.004 (0.134)	-0.057 (0.126)		0.185 (0.251)	0.098 (0.257)		-0.062 (0.222)	-0.073 (0.199)		57
F-test	[0.240]	[0.696]		[0.569]	[0.183]		[0.708]	[0.880]		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows OLS regression estimates of laureate father SES rank on prize year, estimated separately for men and women; by prize discipline; and by childhood region. The coefficients in the average-rank columns can be interpreted as rank point change per year. Coefficients in the top-10% and top-20% indicator columns are percentage points per year, i.e. -0.113 in row 1 indicates an 11.3 percentage point decline in the top-10 share over 100 years. Global income is intentionally left out for regional comparisons because it is not meaningful to compare it across regions. Standard errors are in parentheses. The F test row shows p-values from tests of equality of all subgroup trend coefficients.

Table A13: occ1950 Parent-Field Correspondence

Code	Occupation	N	Field	Code	Occupation	N	Field
<i>A. Professors</i>							
16	Engineering-professors and instructors	6	Physics	10	College presidents and deans	2	No match
23	Physics-professors and instructors	5	Physics	17	Geology and geophysics-professors and instructors	1	No match
13	Biological sciences-professors and instructors	11	Physiology	18	Mathematics-professors and instructors	5	No match
62	Biological scientists	7	Physiology	69	Misc. natural scientists	6	No match
19	Medical sciences-professors and instructors	5	Physiology	26	Natural science (nec)-professors and instructors	1	No match
14	Chemistry-professors and instructors	9	Chemistry	28	Non-scientific subjects-professors and instructors	3	No match
15	Economics-professors and instructors	2	Economics	25	Statistics-professors and instructors	1	No match
27	Social sciences (nec)-professors and instructors	9	Economics	29	Subject not specified-professors and instructors	14	No match
12	Agricultural sciences-professors and instructors	1	No match				
<i>B. Non-Professor Occupations with Technical Links to Nobel Fields</i>							
41	Aeronautical-engineers	2	Physics	68	Physicists	7	Physics
43	Civil-engineers	7	Physics	71	Osteopaths	1	Physiology
44	Electrical-engineers	14	Physics	73	Pharmacists	9	Physiology
49	Engineers (nec)	19	Physics	75	Physicians and surgeons	60	Physiology
45	Industrial-engineers	4	Physics	42	Chemical-engineers	5	Chemistry
46	Mechanical-engineers	6	Physics	7	Chemists	11	Chemistry
48	Mining-engineers	3	Physics	81	Economists	3	Economics
<i>C. Occupations that are Topically Adjacent to Nobel Fields</i>							
550	Automobile-mechanics and repairmen	3	Physics	305	Bank tellers	2	Economics
63	Geologists and geophysicists	1	Physics	201	Buyers and shippers, farm products	6	Economics
541	Locomotive engineers	1	Physics	205	Floormen and floor managers, store	3	Economics
544	Machinists	1	Physics	450	Insurance agents and brokers	11	Economics
604	Machinists and toolmakers apprentice	1	Physics	290	Managers, officials, and proprietors (nec)	108	Economics
554	Mechanics and repairmen (nec)	3	Physics	250	Officials and administrators (nec), public administration	42	Economics
32	Dentists	7	Physiology	280	Purchasing agents and buyers (nec)	1	Economics
82	Psychologists	1	Physiology	470	Real estate agents and brokers	3	Economics
98	Veterinarians	2	Physiology	490	Salesmen and sales clerks (nec)	17	Economics
671	Photographic process workers	1	Chemistry	83	Statisticians and actuaries	1	Economics
0	Accountants and auditors	16	Economics	480	Stock and bond salesmen	4	Economics
<i>D. Other Occupations</i>							
400	Advertising agents and salesmen	5	No match	650	Mine operatives and laborers	1	No match
61	Agricultural scientists	1	No match	57	Musicians and music teachers	2	No match
2	Airplane pilots and navigators	2	No match	240	Officers, pilots, pursers and engineers, ship	2	No match
3	Architects	4	No match	690	Operative and kindred workers (nec)	4	No match
4	Artists and art teachers	3	No match	564	Painters, construction and maintenance	1	No match
6	Authors	1	No match	570	Pattern and model makers, except paper	2	No match

Code	Occupation	N	Field	Code	Occupation	N	Field
500	Bakers	3	No match	74	Photographers	2	No match
504	Brickmasons, stonemasons, and tile setters	3	No match	574	Plumbers and pipe fitters	3	No match
510	Carpenters	12	No match	270	Postmasters	1	No match
511	Cement and concrete finishers	1	No match	575	Pressmen and plate printers, printing	2	No match
9	Clergymen	16	No match	99	Professional, technical and kindred workers (nec)	2	No match
390	Clerical and kindred workers (n.e.c.)	5	No match	674	Sawyers	1	No match
631	Conductors, bus and street railway	1	No match	782	Sheriffs and bailiffs	1	No match
594	Craftsmen and kindred workers (nec)	3	No match	582	Shoemakers and repairers, except factory	1	No match
632	Deliverymen and routemen	1	No match	79	Social and welfare workers, except group	5	No match
36	Editors and reporters	7	No match	675	Spinners, textile	1	No match
840	Farm service laborers, self-employed	1	No match	350	Stenographers, typists, and secretaries	4	No match
100	Farmers (owners and tenants)	22	No match	585	Structural metal workers	2	No match
523	Foremen (nec)	2	No match	92	Surveyors	2	No match
53	Foresters and conservationists	4	No match	681	Switchmen, railroad	3	No match
525	Furriers	4	No match	590	Tailors and tailoresses	4	No match
930	Gardeners, except farm and groundskeepers	1	No match	93	Teachers (n.e.c.)	31	No match
430	Hucksters and peddlers	1	No match	365	Telegraph operators	1	No match
534	Jewelers, watchmakers, goldsmiths, and silver-smiths	3	No match	370	Telephone operators	2	No match
970	Laborers (nec)	1	No match	591	Tinsmiths, coppersmiths, and sheet metal workers	2	No match
643	Laundry and dry cleaning operatives	1	No match	683	Truck and tractor drivers	2	No match
55	Lawyers and judges	29	No match	784	Waiters and waitresses	1	No match
230	Managers and superintendents, building	4	No match	684	Weavers, textile	2	No match
67	Mathematicians	2	No match	685	Welders and flame cutters	1	No match
644	Meat cutters, except slaughter and packing house	2	No match				

Notes: The table shows the assignments made between occupations and scientific disciplines.

B Additional Information on Data and Methods

B.1 Biographical Data

We hand-collected biographical information for every Nobel laureate in physics, chemistry, physiology, and economics. For each laureate, we reviewed multiple sources to identify their birth dates, birth locations, and the occupations of their parents. The availability of parent occupational information was heterogeneous. Many winners described their parents' work in their acceptance speeches or biographies. Parent occupations were also recorded in documents like obituaries, biographies, scientific directories and encyclopedia entries. When we could not find information on father occupation, we reached out to living laureates, a handful of whom responded with information about their parents. We obtained data on father occupations for 714 out of 739 laureates (96.2%), but only 181 mother occupations (25.3%). Mothers' occupations are also generally less informative about laureates' childhood socioeconomic status, because so many women in this era were out of the labor force.

When laureates moved before the age of six, we assigned them to their location at age six. Results were unchanged if we used other ages as anchors for their home country. When laureates were born to expatriates (i.e. parents living temporarily in countries other than their home country), we assigned them to their parents' home countries, as the home country occupational distributions are likely to be more relevant for determining parental rank. We similarly assigned them to home countries when parents were serving in a foreign service. For example, Ronald Ross (physiology, 1902) was the son of a British general serving in India; at age 8, he moved to the Isle of Wight for school. Our assumption is that his parents' socioeconomic status is better characterized by the average status of an army general in the United Kingdom than that of an army general in India. There are only a handful of cases like these, so they do not have a substantial bearing on our results.

We construct cohorts of winners by rounding each winner's birth year to the nearest decade (e.g., a winner born in 1893 belongs to the 1890 cohort, whereas a winner born in 1898 belongs to the 1900 cohort). There are six winners born between 1835 - 1843, all of whom are initially

assigned to the 1840 cohort. However, due to the lack of availability of census data during these years, we then map these observations to 1850 instead, the closest available decade.

B.2 Occupational Earnings and Education from U.S. Population Census

To estimate the socioeconomic status of laureates' parents, we aimed to identify the average income and education ranks of people with the same occupation as each laureate's father in the U.S. Census. We used data from the 1850–1970 U.S. population censuses, extracted from IPUMS and proceeded as follows.

We restricted the census sample to working age (18–65 years old) men, and dropped all individuals who were not in the labor force. We also dropped census observations for which the occupational category variable takes on the following values: “students”, “disabled individuals with no reported occupation”, “other non-occupation”, “n/a (blank)”. Excluding the unemployed could marginally bias our ranks downward, but the bias should be small, given that (i) the historic U.S. unemployment rate has typically fluctuated between only 5–8%; and (ii) the unemployed are distributed across many different occupations, limiting the degree of bias.

We matched each laureate's father occupation to the nearest harmonized occupational category (*occ1950*, created by IPUMS). When fathers held multiple occupations, we assigned the one described as the primary occupation during the laureate's childhood years. Fathers described only as aristocrats or large estate holders, with no more specific occupation reported, were assigned both income and education ranks of 100. Appendix Table B1 shows the list of occupational categories used in the sample.

There is inevitably some measurement error in classifying business owners, as the historical record was often unclear on the scale of the business; as such, a business owner could represent a relatively upper or middle class family. We classified business owners with code 290, which is “Managers, officials, and proprietors, not otherwise classified.” This puts business owners, on average, at the 86th education percentile and the 93rd income percentile. Farm owners exist as an *occ1950* category, but similarly cover a wide range of socioeconomic ranks. To ensure that our

assumptions about these occupational ranks were not driving any of our results, we verified that our primary results are similar when we exclude business owners and farmers (Appendix Tables A5 and A8).

Individual and household earnings were available beginning in 1950, and years of education in 1940, so we used these values for all earlier years. We excluded negative or zero earnings values. Literacy is recorded in earlier census years, but is considered less reliable by historians, as collection methodology varied substantially across enumerators (Collins and Margo, 2006). For census years after 1940/50, we applied a three-census moving average to smooth out fluctuations in occupational income and education from sampling variation and interpolated missing values.³⁰

We also estimated the population share of each occupation in each decade, which is essential for calculating ranks. To calculate ranks, we assigned individuals an earnings level based on their occupation, and then ordered individuals within each decadal census according to those earnings levels. We then assigned the mean earnings rank within each occupation group, and collapsed the data to occupation-decade level. These earnings ranks were then matched to the Nobel laureates database at the occupation-decade level. We performed a similar exercise for education ranks.

Since occupational incomes were not observed before 1950, there is no change in the relative ordering of occupations before 1950. However, we observe the share of people with each occupation in all census years, so the *ranks* of occupations do change continuously over time. For instance, trade workers tended to have relatively high education ranks in 1850, but had lower ranks by 1950, due to the growing number of more educated white collar workers.

B.3 Historical Estimates of Country-Level GDP per Capita and Population

We used country of childhood in two ways in our analysis. For our primary analysis, we used country of childhood to adjust the relative occupational distributions, to reflect the fact that an individual with only some schooling (say, literacy) would occupy a higher education rank in a poor country than in a rich country. Second, for the section on income differences across countries

³⁰These adjustments have little bearing on our results, as they only affect census years after 1940/50, and most Nobel laureates were born earlier.

only, we used national GDP per capita to adjust occupational earnings for living standards across countries. This second adjustment reflects the fact that an individual at the 90th percentile of the earnings distribution in India has a much lower global income rank than an individual at the 90th percentile in the United States.

We used historical estimates of GDP per capita and population for 217 countries from 1830–1970, from Fariss et al. (2022), with adjustments described below.

B.3.1 Adjusting for Occupation Distributions

The distribution of occupational population shares affects the resulting socioeconomic rank of each occupation, even if the ordering of occupations is unchanged. For example, the percentile rank of a sawyer in the U.S. is much higher in 1850, a time when roughly 44% of the population were farmers, compared to 1950, when that share is down to only 9%. Similarly, countries will have different occupational distributions at different levels of economic development. However, we only had data on the historical occupational distribution of the United States.

We therefore used the U.S. historical occupational distribution to proxy for the occupational distribution in other countries at different points in time. We assigned each country the U.S. occupational distribution from the decade when its development level (measured by GDP per capita) was nearest to that of the U.S., using minimum absolute distance.

Consider an example of how we would calculate the earnings rank of an Indian tailor in 1950. First, we identified the U.S. decade in our sample data with the nearest GDP per capita level to that of India in 1950 — this was 1850. In 1850 in the U.S., a tailor had an earnings rank of 84; we assign this rank to the Indian tailor for the primary analysis. By contrast, in the U.S. in 1950, a tailor would have an earnings rank of only 55.

B.3.2 Calculating Global Income Ranks

Our primary analysis focuses on occupational ranks within countries. Since most winners are from the West, this tells us how effective the West is at mobilizing its own talent. In the final part of the results, we instead consider global income ranks, which tell us how effective human society is at

mobilizing global talent. Consider again the Indian tailor in 1950 above. The tailor occupied the 84th earnings rank in India, but their global earnings rank was much lower, since India in 1950 was a very poor country.

We calculate a global earnings rank as follows. First, for each country-decade-occupation group, we scale the occupational income by the GDP per capita ratio of each country with the United States in the same decade. This gives us a real income estimate for each country-decade-occupation group. Second, we create a synthetic global population based on each country's occupation shares (adjusted for development level, as above) and their population. An individual's rank in this synthetic population is that individual's global income rank.

Let us continue with the example of the Indian tailor above. We have already estimated that the tailor is at the 84th earnings percentile in India in 1950. In 1950, U.S. GDP per capita was approximately 16 times higher than Indian GDP; we therefore multiply the Indian tailor's predicted income by 0.06. After conducting this calculation for every country-occupation-decade, the Indian tailor has a global income rank of 46. This reflects the fact that the tailor is relatively well off in India, but India is relatively poor globally. Appendix Figure B1 summarizes the example.

For individuals from poor countries, global ranks are systematically lower than national ranks, and vice versa. A U.S. tailor in 1950 would be at the 97th percentile globally. Since most of the Nobel laureates are from rich countries, the average global earnings rank is therefore higher than the average national earnings rank.

Figure B1: Example Calculation of National and Global Earnings Ranks

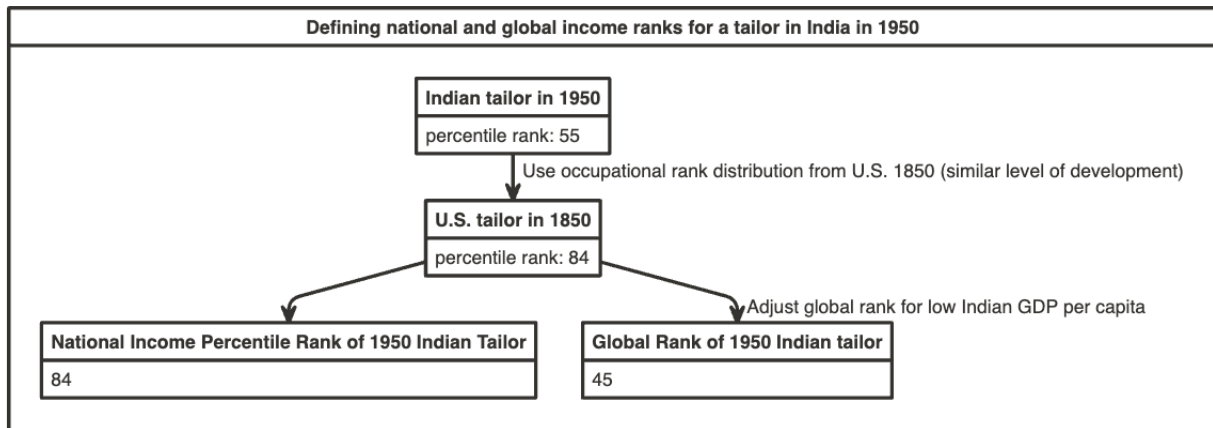


Table B1: List of Occupational Categories Present in the Analysis Sample

Occupation Title	Frequency	Percent
Managers	131	18.37
Professors and instructors	85	11.92
Health professionals	75	10.52
Engineers	61	8.56
Officials, government and non-profit organizations	51	7.15
Jurists	31	4.35
Elementary and secondary school teachers	29	4.07
Farmers and farm managers	23	3.23
Natural scientists	17	2.38
Workers in religion	17	2.38
Accountants	16	2.24
Sales workers and shop assistants	15	2.10
Insurance agents	12	1.68
Craftsmen and kindred workers, n.e.c.	10	1.40
Aristocrats and landowners	9	1.26
Office and clerical workers	9	1.26
Professional, technical, and related workers, n.e.c.	9	1.26
Operatives and kindred workers, n.e.c.	8	1.12
Bricklayers, carpenters, and related construction workers	7	0.98
Journalists, authors, and related writers	7	0.98
Creative artists	6	0.84
Commercial Managers	5	0.70
Other agents	5	0.70
Printers and related workers	5	0.70
Tailors and related workers	5	0.70
Architects	4	0.56
Jewelers, opticians, and precious metal workers	4	0.56
Bakers	3	0.42
Blacksmiths and machinists	3	0.42
Bookkeepers and related workers	3	0.42
Building managers and proprietors	3	0.42
Butchers	3	0.42
Plumbers and pipe-fitters	3	0.42
Vehicle mechanics	3	0.42
Electronics service and repair workers	2	0.28
Foremen	2	0.28
Gardeners	2	0.28
Other mechanics	2	0.28
Painters	2	0.28
Real estate agents	2	0.28
Social and welfare workers	2	0.28
Statistical and social scientists	2	0.28
Textile workers	2	0.28
Truck drivers	2	0.28
Welders and related metal workers	2	0.28
Aircraft pilots and navigators	1	0.14
Cabinetmakers	1	0.14
Farm laborers	1	0.14
Fishermen	1	0.14
Food service workers	1	0.14
Launderers and dry-cleaners	1	0.14
Locomotive operators	1	0.14
Miners and related workers	1	0.14
Nonmedical technicians	1	0.14
Postal and mail distribution clerks	1	0.14
Protective service workers	1	0.14
Sawyers and lumber inspectors	1	0.14
Ship officers	1	0.14
Telephone operators	1	0.14

Notes: The table lists the occupational categories (according to the 1950 census classification) in our analysis sample and their frequency among the Nobel laureates' fathers.