The Scientist in the Machine Age*

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Abstract

Artificial intelligence can make science more widely accessible without making scientific careers more widely available. I distinguish the ability to produce research, the pay and recognition it earns, and the ability to afford a research career. The machine lowers the skill barrier, allowing more people to produce research. But wages can fall when machines substitute for human labour and research budgets do not keep pace. Recognition depends on relative standing, with professional networks dividing a fixed pool. A salaried university career is sustainable only when pay, recognition and income from wealth together cover a minimum standard of living. In the central case, with recognition held equal and constant, more people can do science while fewer can earn a living from it. Those who remain are disproportionately wealthy. If abundant output makes reputation the filter through which work is read, recognition shifts towards the well-connected relative to the poorly connected. Researchers paid closest to subsistence face the greatest pressure: in practice, those on fixed-term contracts and at the periphery of their fields. Four episodes illustrate the distinction between doing science and sustaining a career: professionalisation, gentleman science, chess after the engines and citizen astronomy. United States data show that pressure on paid posts predates the machine. The model assumes that every capable person produces research, paid or not. Research can therefore spread while the paid profession contracts. Wealth cushions a fall in pay; connections shape who receives credit.

Keywords: scientific careers; artificial intelligence; recognition; professionalisation; research evaluation; inequality in science

JEL codes: J24; J44; O31; O33; I23

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1 More research, fewer scientists?

Charles Darwin never received a salary for doing science. Robert Boyle and Henry Cavendish financed their work from private wealth. Before the nineteenth century, independent wealth sustained many of those who advanced organised knowledge. The salaried research career is a recent institution. Daniels (1967) dates the professionalisation of American science to the decades before the Civil War. Yet Lucier (2009) shows that, in nineteenth-century America, professional and scientist expressed different relations to commerce. The professional sold scientific services; the scientist claimed independence from commercial demands. In this vocabulary, a professional scientist was a contradiction in terms. Salaried scientific posts existed in colleges and government surveys. What had to be created was a research career that combined a salary, a credential and an expectation of discovery.

Artificial intelligence now appears to widen access to science again. I can ask a machine a question that, only a year ago, would have required a research assistant, a year of work and a grant I did not have. I receive an answer within a few hours. The gain is largest where capacity was scarcest. A colleague at a leading department has always had graduate students and a well-stocked library. At a university far from those centres, the constraint was never a shortage of questions. It was a shortage of capacity. Now, much of that constraint has eased. The natural conclusion is that artificial intelligence democratises science. This paper asks what that gain means for scientific careers. I build a small model that separates the ability to produce research from the rewards it earns and the ability to afford a career. Four historical episodes help explain why these distinctions matter. The body of the paper states the assumptions and results in words. Appendix A gives the equations.

Being able to do research does not, by itself, provide a livelihood. A career depends on pay and on the credit that helps a researcher secure appointments, prizes and further opportunities. Neither follows automatically from the ability to do the work. A market determines the pay. A profession allocates the credit. The career in this paper is the salaried university post. Public discussion often treats three different questions as one: whether a person can produce research at all, which I call capability; what a research career pays and what recognition it earns, which I call the career return; and whether a person can afford to sustain the career, which I call participation. More people able to do research need not mean more people paid to do it.

In the model, people differ in innate skill, wealth and position in professional networks. Artificial intelligence raises effective skill, with the largest gains among the least skilled. The innate skill needed to produce research with machine help therefore falls, allowing the capable population to grow. The career return has two parts. The first is the wage, set in a labour market in which human hours and machine services interact. When the machine performs much of the work previously done by a human hour and the research budget does not grow to match, the wage falls. The second is recognition: placement in leading journals, prizes, invitations and the attention of other researchers. It is positional, a fixed set of ranks that professional networks divide. A person can sustain a career only if the wage, recognition and income from wealth together meet a minimum consumption level.

Two results follow. The first concerns the number of scientists. When machines substitute for human research labour, the budget does not keep pace and recognition is held equal across people and constant, more people can do science while fewer can afford to do it for a living. Those who remain are disproportionately wealthy. The gap between these two groups is the capability–participation wedge shown in Fig. 1. The second result concerns composition. If abundant output makes reputation the main filter through which work is read, a fixed set of ranks divided among a growing number of capable people shifts towards the well-connected. When recognition is distributed equally, wealth determines how many people can sustain a career. But recognition is not distributed equally. Who receives recognition therefore matters for who can stay. The model does not, however, predict whether unequal recognition raises or lowers the total number of participants. Both results show up first among the researchers paid closest to subsistence and holding the least private wealth: in practice, staff on fixed-term posts and those at the periphery of the research system. The risk posed by artificial intelligence is not that fewer people will be able to do science. It is that the two scarce returns that make science a career will remain with those who were already advantaged.

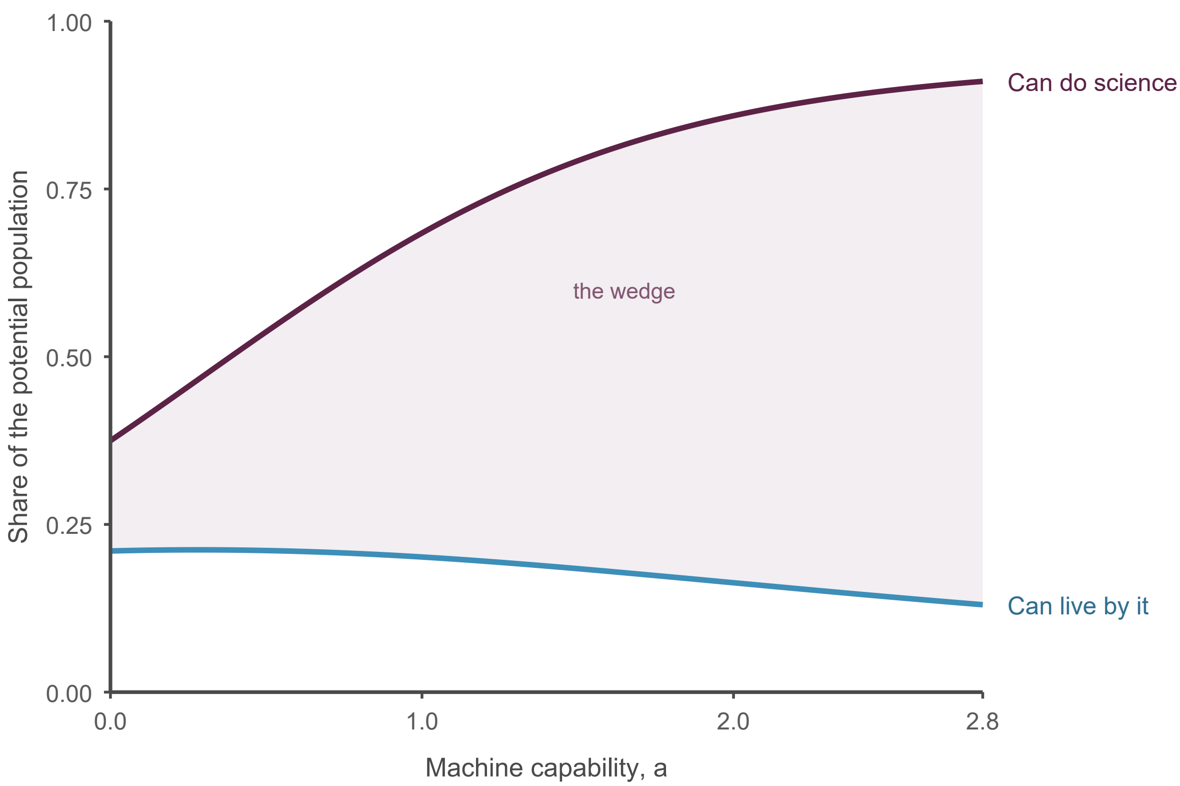

Fig. 1 The capability–participation wedge. Illustrative simulation of the model in Appendix A ($\sigma > 1$, flat budget). Capability expands throughout; paid participation rises slightly at first, then falls.

The argument draws on three bodies of research. The first is the history and sociology of the scientific vocation. Polanyi (1962) described a republic of science in which authority and recognition are conferred by overlapping neighbourhoods of competent judges. Merton (1968) showed that the credit so conferred accumulates. Shapin (2008) traced how the vocation became a salaried post, and Daniels (1967), Lucier (2009) and Morrell and Thackray (1981) describe the earlier forms of that transition. I add a labour market to this account. Pay and recognition are then set by different mechanisms, and a technology can change one without changing the other. The second literature studies artificial intelligence as a method of invention (Cockburn, Henderson and Stern 2019; Bianchini, Müller and Pelletier 2022). It asks what the machine does to the rate and direction of discovery, and finds automated tools raising research output (Furman and Teodoridis 2020) while compressing skill (Noy and Zhang 2023; Brynjolfsson, Li and Raymond 2025). I ask instead what the machine does to the profession that discovers, and show that the population producing research and the profession paid for it can move in opposite directions. The third literature studies research careers and their evaluation. It has documented hyper-competition and narrowing notions of worth among doctoral and postdoctoral researchers (Fochler, Felt and Müller 2016; Nästesjö 2025), an oversupply of doctorates relative to posts (Alberts et al. 2014; Larson, Ghaffarzadegan and Xue 2014), the economics of the scientific labour market (Stephan 2012; Stern 2004) and the distortions that metrics produce (Hicks et al. 2015; Wilsdon et al. 2015; Azagra-Caro and Tur-Porcar 2026). The model offers a mechanism that connects these observations. It shows when rising research output can cease to be a useful guide to the health of the profession. United States data show the pressure on paid posts that preceded the machine: doctorates awarded have grown for six decades while the share of academically employed science, engineering and health doctorate holders in full-time faculty posts has fallen.

Section 2 presents four historical episodes in which doing research and earning a living from it were distinct questions. Section 3 states the model in words, Section 4 gives its results and where they bind first, and Section 5 draws the implications for research evaluation and policy. Section 6 concludes. Appendix A contains the equations.

2 Four settings, one career question

New technology can make research easier without making a research career easier to sustain. What remains scarce, and who controls access to it? Four episodes help answer that question. Two involve machines and two do not. The distinction matters because the argument does not depend on a machine: a change in the cost of research or in what a career pays can separate the ability to do the work from the ability to live by it. For each episode, I ask what became easier to produce, what remained scarce, who retained the advantage and whether the change affected the number of scientists or their composition. Fig. 2 simulates each pattern with the model in Appendix A. Each panel illustrates a different change: the budget over time for professionalisation; the salary on offer for gentleman science, set outside the model to represent the limited availability of paid research careers; and machine capability for chess and citizen astronomy.

Daniels (1967) dates the emergence of professional American science to the four decades before the Civil War. Salaried scientific posts already existed, but Lucier (2009) shows that professional and scientist expressed different relations to commerce. The professional sold scientific services; the scientist claimed independence from commercial demands. The research universities that followed helped establish the salaried research career. Shapin (2008) traces the later history of that role: the calling described by Weber became, over the twentieth century, an ordinary salaried job in universities and industrial laboratories. In the model, this expansion is represented by a sustained positive η_B, the growth rate of the research budget. In the United States and Western Europe, budgets and paid posts expanded for about a century. Budget growth raised the demand for research labour, so the number of paid scientists increased. Professionalisation also expanded and reshaped the institutions that allocated recognition. Learned societies and scientific journals had existed since the seventeenth century (Royal Society n.d.*a*). Increasingly refereed journals, appointments and letters of reference distributed credit through professional networks. This episode illustrates the network-based allocation described by the model. The argument of this paper is that artificial intelligence can reverse the expansion of paid careers.

Before salaried posts became common, science was often done by people who could afford it. Darwin held no paid scientific position. Boyle lived on the income from his family's estates. Cavendish financed his laboratory from one of the largest private fortunes in Britain. Capability was not the constraint: these men were among the most capable people of their time. Recognition flowed through clubs, correspondence and patronage. These channels reflected social position, and wealth bought access to them. Morrell and Thackray (1981) show how the British Association for the Advancement of Science, founded in 1831, was organised by and for such men: gentlemen whose income, standing and mutual acquaintance decided who could speak for science. Wealth and connection were therefore related rather than separate barriers. Behind the gentlemen stood a second group. Shapin (1989) shows that Boyle's experiments were performed largely by paid technicians whom his published accounts rarely name. Capable work without credit is therefore older than the machine. Paid scientific posts existed, but they offered a narrow route into an independent research career. Hooke's paid curatorship at the Royal Society is an early example (Royal Society n.d.*b*). Where pay was insufficient to support a research career, private wealth could cover the gap. When the wage is low, only those whose private resources cover the shortfall can sustain the work. Wealth, with the restrictions of class and gender that accompanied it, determined who could take part. The model shows how strong substitution (a high σ) and slow budget growth (a low η_B) can again favour those with private wealth.

In 1997, a machine defeated the world chess champion. Within a decade, engines played better than every human. Strong analysis became easier to produce. Players with access to engines improved, and the gains were confined to players weaker than the machine. The distribution of playing strength therefore converged (Gaessler and Piezunka 2023). Engines made strong analysis widely available. Adjournments largely disappeared from elite play during the 1990s (United States Chess Federation n.d.). At the top of correspondence chess, draws became overwhelmingly common: the 33rd world championship final ended in 2025 with 126 draws and ten wins awarded by default (International Correspondence Chess Federation 2025). Yet human preparation and coaching retained a role. FIDE's account of the 2024 world championship credits Gukesh's team for an opening that caught his opponent by surprise (International Chess Federation 2024). Chess illustrates the automation of an analytical task; it does not establish a fall in the number of paid analysts. The high-σ, flat-budget panel in Fig. 2 therefore illustrates a possible labour-market consequence rather than an estimated history of chess employment. Networks continue to allocate invitations, coaching and visibility. They can shape access to competition and preparation, even though the results of games are decided over the board. The argument about recognition applies most directly to the careers built around chess.

Amateurs contributed to astronomy long before modern machines, and the boundary between paid and unpaid observers has been contested for more than a century (Lankford 1981; Rothenberg 1981). Cheap detectors and public archives lowered the skill and access thresholds further. Hundreds of thousands of volunteers now perform genuine classification and discovery (Marshall, Lintott and Fletcher 2015). Citizen astronomy shows that widespread unpaid contribution can coexist with professional research. The model represents this possibility with a low effective σ. Machine classifiers handle routine cases, but people must still design the survey, adjudicate classifications and turn the results into science. The episode is consistent with complementarity in research activity, but does not isolate the mechanism or establish its effect on paid employment. Professionals may perform tasks that classifiers do not affect, and their employment also depends on research budgets. A second example comes from computer science. When a consumer motion sensor unexpectedly automated tasks in motion-sensing research, Furman and Teodoridis (2020) find that researchers produced more work and pursued a wider range of ideas. These findings support complementarity in research activity, without establishing its effect on paid employment. Networks can also operate in the opposite direction in these settings. Platforms and professional co-authorship can connect an outsider to recognition by certifying a volunteer's discovery rather than excluding her from it.

Across these episodes, doing the work and sustaining a career depended on different resources. Research budgets funded pay, private wealth covered shortfalls, and connections helped secure recognition. Machines can assist researchers as well as replace their tasks. A growing research population and a shrinking paid profession are therefore one possible outcome, not an inevitable one. The model sets out the conditions under which they occur together.

3 Capability, career return and participation

The model asks who can do research, what a research post pays and who can afford to hold one. This section explains the mechanism in words, using one equation to show what makes a career affordable. Appendix A gives the formal assumptions, equations and proofs.

Let a denote the capability of the best available machine. It rises over time. A person has

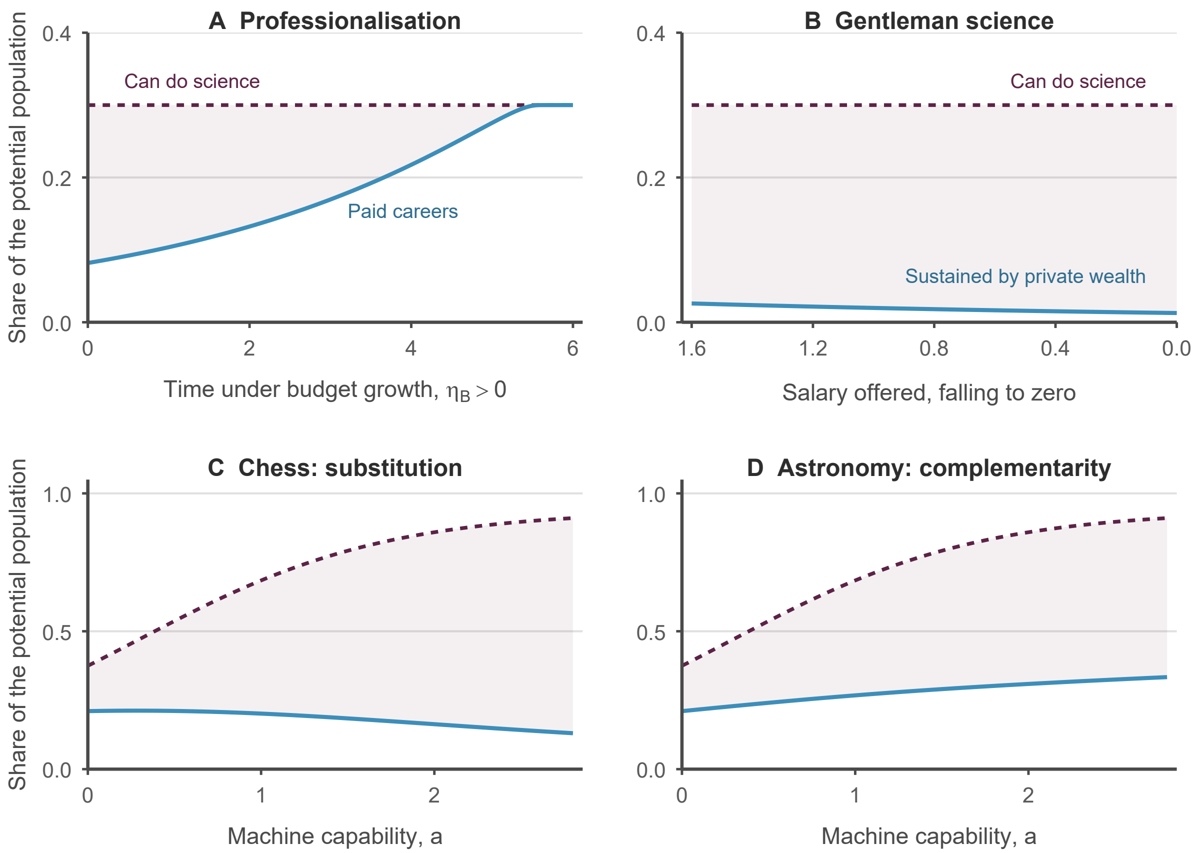

Fig. 2 One model, four settings. Each panel varies a model parameter associated with the setting. Dashed line: share who can do science; solid line: share who can sustain the work. The chess panel illustrates substitution with a flat budget; the astronomy panel illustrates complementarity with modest budget growth ($\eta_B = 0.04$). These are model illustrations, not historical employment estimates.

innate skill, wealth and a position in professional networks. Access to the machine costs a flow κ per period, and wealth earns a return r, so access is affordable when the income from wealth covers the access cost. The machine raises effective skill by a fraction of the distance between a person's innate skill and full skill. The gain is therefore largest for the least skilled. Recent experiments find this pattern: generative tools raise the output of the least experienced workers most (Noy and Zhang 2023; Brynjolfsson, Li and Raymond 2025). Producing research requires effective skill above a fixed threshold. As the machine improves, and as long as the threshold has not been saturated, the lowest innate skill that clears it with machine help falls, and a mass of people becomes newly capable. The capable population is the incumbents who cleared the threshold without the machine plus the newly capable who can afford access. An incumbent remains capable without the machine; whether she can afford a post that uses it is a separate question, settled by the participation constraint below. When skill and wealth are independent, the capable population grows whenever access becomes cheaper. It can grow even when access becomes dearer, provided the skill gain is large enough (condition C in the appendix). Making more people capable is therefore the easier part of the argument. Whether they can afford a career depends on what that career pays.

Capability determines who is eligible to work. The labour market determines what a research post pays. Research services combine human labour and machine services with a constant elasticity of substitution σ. When σ exceeds one, the two inputs are substitutes, and a cheaper machine reduces spending on human labour. When σ is below one, they are complements, and a cheaper machine raises that spending. The machine's price falls over time. The research budget grows at a rate η_B. Labour demand therefore rises with budget growth and falls with displacement when machines substitute for human labour (equation R1 in the appendix). The effective elasticity is not determined by the technology alone. Cheap machine production raises the demand for human judgement because someone must verify what the machine produces. This verification premium moves the inputs towards complementarity and reduces the effective σ (Fourie 2026*b*). It can preserve a paid human role, but that role is one of checking rather than producing. In the model, making more people capable does not itself create demand for their labour. It widens the pool of people who can offer research time; the market determines what that time pays.

Each paid post supplies one unit of labour, so labour supply is the number of participants. Equating supply and demand gives the response of the cash wage to the machine (equation R3 in the appendix). Holding the other forces fixed, budget growth raises the wage, displacement lowers it when machines substitute for human labour, entry by the newly capable lowers it, and a higher access cost raises it by excluding participants. Participation moderates these effects. When the wage falls, some researchers leave. Their departure reduces the supply of research labour and supports the wage. Recognition is funded separately from the wage bill, and the rest of the model is in partial equilibrium.

Research also provides two amenities. The first is the pleasure of the work, which the machine raises. The second is attributable meaning, the sense that the result depended on the researcher, which the machine lowers by improving what would have been produced without her. Smith (1776) observed that more pleasant work is paid less; Gans (2026) argues that lost meaning must be compensated with pay. Those forces matter when willingness to work determines labour supply. Here each paid post supplies one unit of labour, and anyone who can afford the career is assumed to want it. Amenities enter that willingness condition. They do not change the wage while the condition remains slack. The central result concerns affordability.

The second part of the career return is recognition. Its scarce element is rank. Fixed prizes, editorial slots and the attention of other researchers are allocated by relative standing (Lazear and Rosen 1981), and much of what a research career pays is positional in this sense. With a fixed number of prizes and a growing capable population, the average chance of winning one falls, however much the volume of published work grows; who bears the fall depends on the allocation. The model represents this positional return as a fixed pool divided among the capable, and networks determine its division. Submissions to the top five economics journals roughly doubled over two decades, while the number of published articles fell (Card and DellaVigna 2013). Journals ration access to the pool with time and money (Fourie 2026*a*). Connections shape the allocation: in the leading general-interest economics journals, more than two-fifths of published articles are written by authors connected to a serving editor (Colussi 2018). Sociologists of science described this allocation before economists modelled it. Polanyi (1962) saw recognition conferred through overlapping neighbourhoods of competent judges, which is a network; Bourdieu (1975) called the standing so accumulated scientific capital; and Latour and Woolgar (1986) described a credibility cycle in which credit converts into resources and back into credit. The career return in this paper is the economic form of that cycle. Network position affects only the allocation of recognition. It does not enter capability or labour demand directly. Recognition can nevertheless affect the equilibrium wage through participation.

Two assumptions matter for how recognition is distributed. First, every capable person produces research and competes for recognition, whether or not a budget pays her. This is a maintained assumption, not a result of the model. Shapin's technician offers a historical example of work that was done without the recognition accorded to an independent scientist. If only paid researchers competed, fewer paid researchers would mean more recognition per survivor. That could partly offset the financial pressure to leave, although the overall effect on participation is not determined. Here the pool is divided among everyone capable of research. Second, a parameter ρ determines whether networks become more or less important as output becomes abundant. Its sign is not fixed. The machine may substitute for the network. A procedure might assess work without regard to its author, or an assistant might connect an unknown researcher to editors. In that case $\rho < 0$, the weights that allocate recognition flatten, and recognition among a given set of people is distributed more equally. Alternatively, abundant output may make reputation the only practical filter. Attention has scale economies, so small differences in standing can command disproportionate shares of it (Rosen 1981). In that case $\rho > 0$, the weights steepen, and recognition among a given set of people becomes more concentrated among the best-connected. Merton (1968) described this cumulative advantage.

The affordability calculation rests on three assumptions. First, a paid research post is full time. A participant supplies one unit of labour per period and receives the salary w. Every term in the constraint below is therefore measured as income, or its consumption equivalent, per period. Second, recognition has a monetary component. The recognition b_i below is the monetised part of standing: the appointments, prizes and honoraria that follow placement and attention. It is measured net of the wage and of any amount funded from the research budget, so no return is counted twice. Third, access to the machine is part of the job. Frontier research after the machine requires that access, so every participant pays κ, including incumbents who were capable before the machine.

For someone capable of doing the work, a career is affordable when pay, recognition and income from wealth cover a minimum standard of living, $\underline{c}$, and the cost of machine access:

$$\text{participate} \iff w + b_i + rW_i \;\geq\; \underline{c} + \kappa. \tag{1}$$

Here w is the salary, b_i the monetised recognition of person i, W_i her wealth, r the return on wealth, $\underline{c}$ the consumption floor and κ the cost of machine access. The wage and recognition enter the same constraint. Wealth is the private buffer that covers any shortfall. I assume throughout that anyone who can afford the career wants it, because the career return net of the access cost, plus the amenities of holding a post, exceeds the value of the outside option. Affordability is therefore the binding constraint, and to earn a living from research means, throughout this paper, to be able to sustain a salaried post from its salary, its recognition and one's own wealth. The constraint defines a wealth cutoff that falls with the wage and with recognition and rises with the access cost. When recognition is equal across people and constant, the cutoff depends on wealth alone, and total paid participation is the eligible population, incumbents plus those whose skill the machine raises above the threshold, multiplied by the share whose wealth exceeds the career cutoff; because that cutoff lies above the access cutoff, no separate access condition is needed (equation P3 in the appendix). Constant recognition is a benchmark rather than the fixed-pool case. If the fixed pool is instead divided equally among a growing capable population, recognition per person falls. At a common baseline wage and recognition level, the appendix shows that the cutoff rises faster and contraction is at least as easy; the conditions of the central result are then sufficient rather than necessary. A paid research post throughout is a salaried university position funded from the research budget. Employment in a corporate laboratory is part of the outside option. Heterogeneous recognition lowers the cutoff for the well-connected and changes both the number and the composition of participants. Its effect on composition is the second result below; its effect on the total number has no general sign, so the level result is stated under equal recognition.

Consider two people with the same skill and the same preference for research. They differ only in wealth and connection. All values are illustrative. The required skill is 0.7. The machine raises effective skill by one half of the remaining distance. A person with innate skill 0.5 therefore reaches 0.75 and clears the threshold. Before the machine, she did not. Both people are now capable. The salary is $w = 4$, machine access costs $\kappa = 2$, the return on wealth is $r = 0.05$ and the consumption floor is $\underline{c} = 8$. A salary of 4 against a floor of 8 describes a fixed-term post paid near subsistence, not a tenured chair. First set recognition to zero. The first person has wealth of 60. Her income is $4 - 2 + 0.05 \times 60 = 5$, which is below 8. She can do research but cannot earn a living from it. The second person has wealth of 200. Her income is $4 - 2 + 0.05 \times 200 = 12$, which is above 8. She can therefore sustain the career. Now allow recognition to differ. The well-connected second person receives recognition with a larger value, which lowers her cutoff further. The first person is poorly connected and receives almost none. In this example, the person with the private means to sustain the career also receives more of the credit.

4 Results: expansion, contraction and sorting

More people become capable of research when machine access gets cheaper, or when the skill gain outweighs any increase in its cost. More people in more places can produce research. This part of the popular account is correct, and the growth is already visible. Monthly submissions to arXiv, the preprint server that began in physics, rose from a handful in 1991 to more than twenty-four thousand today (arXiv 2026).

A lower wage raises the wealth required to sustain a career. Combining the capability condition with the participation identity gives the central result. Suppose that skill and wealth are independent and that incumbents and the newly capable draw wealth from the same distribution. Suppose also that every participant pays the access cost, that recognition is equal across people and constant, and that anyone who can afford the career wants it. The regularity conditions listed in the appendix must also hold: a smooth wealth distribution, both cutoffs inside its support, a career cutoff above the access cutoff and a positive wage. Then artificial intelligence expands capability while reducing total paid participation if and only if two conditions hold. First, the skill gain outruns any rise in the cost of access, so that the capable population grows. Second, the participation cutoff rises faster than entry adds participants. The rise in the net cost of a career, the change in the access cost less the change in the wage, scaled by the fraction of current participants whose wealth is just at the cutoff, exceeds the rate at which the newly capable join the population. In plainer terms, the wage must fall relative to the cost of access by enough, given how many participants are just at the wealth cutoff, to outweigh the inflow of the newly capable. The wage itself need not fall if access becomes dearer. Appendix A states this as Theorem 1, together with a version (condition F′) that does not contain the wage response.

The theorem makes the trade-off precise. The outcome depends on how readily machines replace human labour, how quickly budgets grow, what access costs and how many people the machine makes capable. It also depends on how many researchers have wealth close to the minimum needed to stay. Three further points follow from it. Total paid participation contracts under a less demanding condition than paid participation among the newly capable alone, because the newly capable are a smaller share of the total. Whenever the newly capable margin contracts, total participation also contracts. Contraction is feasible only when displacement and any rise in the cost of access together outweigh budget growth and any fall in the cost of access. When they do not, no rate of capability growth produces contraction. This is the formal sense in which sufficiently rapid budget growth or sufficiently strong complementarity closes this gap. Fig. 3 plots the two contraction boundaries against substitutability and budget growth. The band between them is the case in which total paid participation contracts even though paid participation among the newly capable continues to grow.

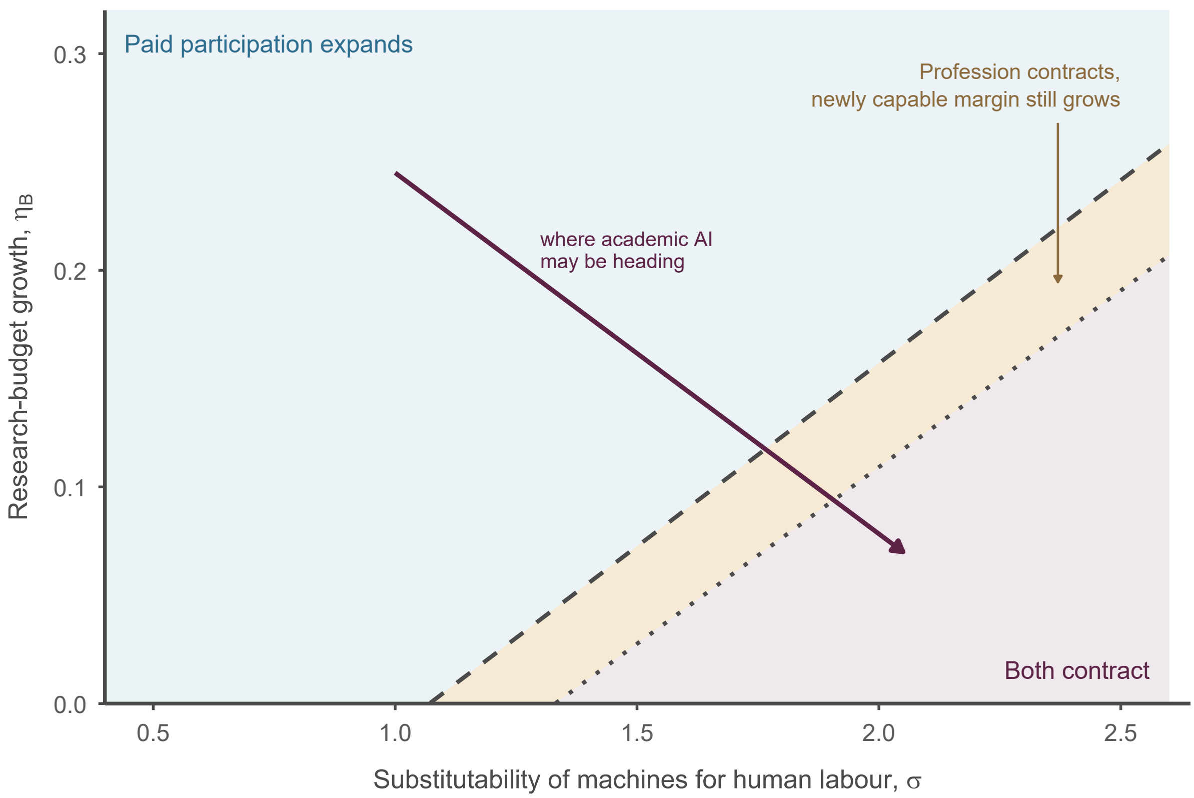

Fig. 3 The participation regime. Separately calibrated local illustration, holding the other model quantities fixed; not a point on the trajectory in Fig. 1. Dashed line: total paid participation unchanged; dotted line: the newly capable margin unchanged. Between the lines, total participation contracts while the newly capable margin still grows. The plum arrow is a conjecture, not an estimate.

Pay and private wealth drive this result. The theorem holds recognition equal and constant; the next result asks what changes when recognition differs across people. People excluded from the paid profession need not stop producing research; the model assumes that every capable person produces, whether paid or not. Whether the machine also makes the marginal researcher more willing to hold a post depends on the wage, the access cost and the balance between greater pleasure and less meaning, and the model does not predict which effect dominates. It makes no claim about the volume of unpaid work.

Affordability determines how many people can sustain a career. Recognition also affects who can stay. Recognition lowers the participation cutoff in (1), and therefore relaxes the constraint most for the well-connected. When $\rho > 0$, the recognition of the better-connected relative to the poorly connected, among those who remain capable, also rises as capability expands. These two effects reinforce each other. Two statements are exact (Proposition 1 in the appendix). First, for any two people who remain capable, the ratio of their recognition rises with the machine in favour of the better-connected, regardless of who else enters. Second, holding the capable set fixed, a person's share of the pool rises if and only if her network position exceeds the recognition-weighted geometric mean of network positions. The top of the network distribution gains share and the bottom loses share. A type in the middle can lose share to the top even while its recognition rises relative to the bottom. When the capable set grows, entry by the poorly connected lowers that mean, which raises the response of every incumbent's share to the network parameter, but entry also enlarges the number of people who divide the pool. A larger advantage over the poorly connected does not, then, guarantee a larger share of the whole pool. That also depends on who enters.

Fig. 4 shows how the fixed pool is divided when the capable set is held fixed and networks become more important. The total remains the same, but the allocation becomes more unequal: the best-connected fifth receives a rising share. Recognition can also change participation. If the common change in the career cutoff lies between the recognition gains of a high- and a low-network type, each converted into wealth by dividing by the return on wealth, the cutoff falls for the high type and rises for the low type. Among a fixed population of each type, participation becomes easier for the high type and harder for the low type. This does not establish that the remaining participants are wealthier. A lower cutoff can admit poorer members of the better-connected group, even when wealth and connection are positively related. The effect on the wealth distribution of participants requires further restrictions.

The two results answer different questions. With equal recognition, a higher wealth cutoff excludes those with the fewest private resources. When recognition differs, professional connections also shape who receives credit and who can afford a career. Without further assumptions, the model does not say whether this raises or lowers the number of careers, or whether those who hold them become wealthier. Professionalisation expanded the institutions that allocate credit (Section 2); those institutions can now make connection more important to a career as machine capability spreads.

The participation constraint bites hardest for researchers whose salary is closest to the consumption floor and who hold little private wealth. That is not the tenured professor. It is the postdoctoral researcher and the lecturer on a fixed-term contract. It is the researcher at a university far from the centres of a field, where the salary is lower in real terms and the access cost is the same. The research system entered the machine age with many early-career researchers already under financial pressure. Doctorates awarded grew faster than the posts that could absorb them, so that each faculty member trained many more doctoral students than the one needed to replace her (Alberts et al. 2014; Larson, Ghaffarzadegan and Xue 2014). Doctoral and postdoctoral re-

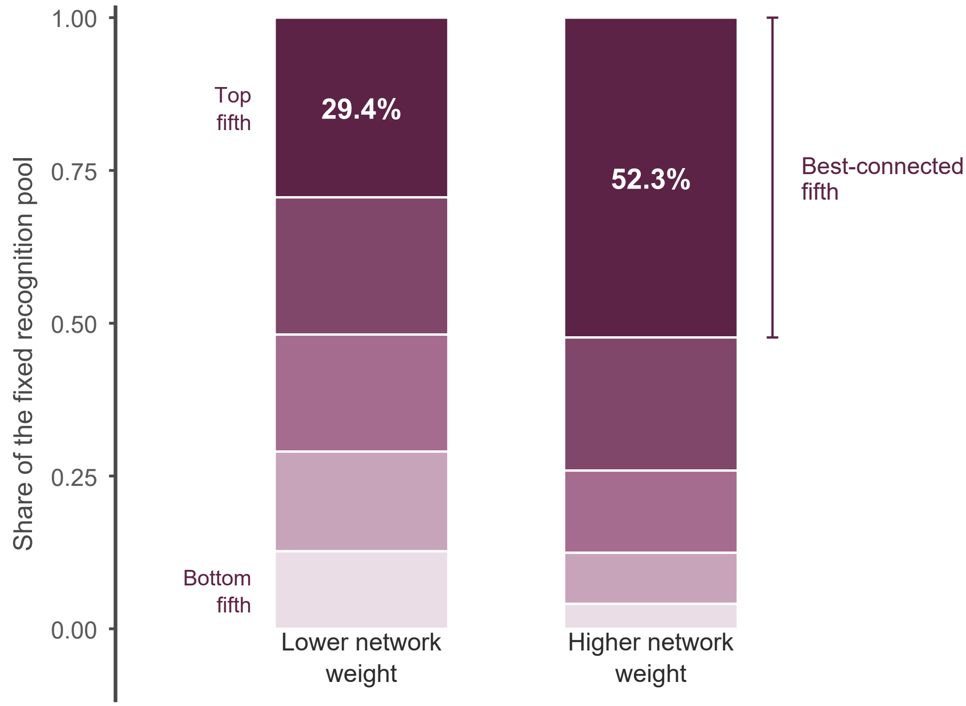

Fig. 4 The recognition pool becomes more concentrated. Share of the fixed pool by network-capital quintile, holding the capable set fixed. Illustrative simulation ($\rho > 0$).

searchers describe the result as hyper-competition, in which the worth of a scientist narrows to the grants and publications she can deliver on a project clock (Fochler, Felt and Müller 2016; Nästesjö 2025). Those who reach the tenure track come disproportionately from high-income and highly educated families (Morgan et al. 2022). The model has one wage and one consumption floor, so it cannot compare postdocs with professors directly. It does show that a wage fall raises everyone's wealth cutoff by the same amount, excluding first those whose wealth is closest to it. Applied to actual careers, this suggests that postdocs are more exposed than established professors. In the model the wealth is the person's own; for a postdoc it is in practice the family's. The recognition that concentrates is the recognition that already flows to the well-connected. Fields with tenured majorities, growing budgets and complementary machines may see none of this for a long time. On this reading, researchers on insecure contracts and far from the centres of their fields face the pressure first.

5 Implications for research evaluation and policy

No single study has estimated the full mechanism. Existing studies provide evidence for its components, although they cover different tasks, workers and settings. Researchers accept lower pay in exchange for the freedom to do science (Stern 2004; Sauermann and Roach 2014; Cassar and Meier 2018). Artificial intelligence increases the pleasure of the work (Noy and Zhang 2023), but reduces the sense of ownership (Gans 2026; Ranjit et al. 2026). It compresses skill (Brynjolfsson, Li and Raymond 2025; Doshi and Hauser 2024). Wages can fall, and prior standing does not protect against that fall (Hui, Reshef and Zhou 2024). Entry is contracting for young workers in exposed fields (Brynjolfsson, Chandar and Chen 2025). None of these changes is yet visible in aggregate pay (Humlum and Vestergaard 2025).

The argument extends beyond artificial intelligence. Any innovation that lowers a skill barrier can allow more people to do the work without supporting more careers, if funding and opportunities for recognition fail to grow with the number capable of doing it. Artificial intelligence is the current example. The cheap telescope and the chess engine are earlier examples. The professionalisation of science is the same mechanism operating in the opposite direction.

Concern about research measurement is not new. The Leiden Manifesto set out principles for using metrics without allowing them to replace judgement (Hicks et al. 2015). The Metric Tide reached a similar conclusion for the United Kingdom's research assessment system (Wilsdon et al. 2015). This paper adds a mechanism to those critiques. Rising output can coexist with fewer paid posts, so an output measure alone can miss a deterioration in researchers' ability to sustain their careers. It also identifies the quantities that determine this result: σ, η_B, κ and ρ. All four can be measured.

The model contains one budget and one sector of salaried posts: the university research career. Firms increasingly fund frontier research in exposed fields (Ahmed, Wahed and Thompson 2023), and they employ a growing number of frontier researchers, including economists who have moved from university faculties (Athey and Luca 2019). The same affordability calculation can be applied to corporate research, using its own budget, pay and wealth cutoff. The model does not explain which sector researchers choose or how they move between them. Different rates of budget growth can place the university and corporate sectors on opposite sides of the boundaries in Fig. 3. Total paid research employment therefore need not fall when university employment contracts. The observed change may instead be a shift in sectoral composition, and an evaluation that relies on university indicators could record that shift as an aggregate contraction. A corporate offer also raises the outside option of the researcher a firm recruits, a margin the model holds slack and does not analyse.

Corporate researchers who publish in the same journals compete for the same scarce recognition, so the argument about its allocation applies to them too. Whether their entry concentrates recognition depends on their network positions (Proposition 1); entry by the well-connected does not, by itself, imply greater concentration.

Testing the argument requires measuring the forces separately. The substitution parameter σ is an elasticity. It describes how spending shifts between human hours and machine services as the machine becomes cheaper, and it can be identified from the response of a field's human cost share to the falling machine price. Task exposure measures something different: the share of a field's research tasks that the machine can perform. Exposure indices already exist for occupations (Autor, Levy and Murnane 2003) and can be constructed for research fields. They suggest where substitution may matter, but do not measure how readily machines and human labour replace one another. Budget growth η_B is the growth rate of a field's real funding and is already collected. Access cost κ is the price of the machine capability required for the work. Recognition concentration is the extent to which network position predicts who is cited, invited and published.

Following research fields over time would help test where these conditions hold. For each field, measure task exposure and, where cost-share data permit, the effective σ. Interact these measures with growth in the field's real funding. Where exposure proxies substitution, the model predicts that high exposure combined with slow funding growth reduces research earnings and paid posts. Its distinctive predictions concern composition. Under equal recognition, a rising career cutoff selects participants by wealth. Proposition 1 separately identifies conditions under which participation becomes easier for a high-network type and harder for a low-network type. The relationships with wealth and with professional connections should be measured separately. The design that Furman and Teodoridis (2020) used for one automated research tool, following the trajectories of the researchers exposed to it against those who were not, is the template at the level of the person. Linked administrative and bibliometric data can measure all three outcomes. The same panel should record the sectoral composition of paid research employment from linked employment records, so that movement between sectors is not read as a decline in the total.

The prediction has a weak form, a strong form and a composition form. The weak form is a fall in the share of trained researchers who hold a paid post while research output rises. The strong form is a fall in the number of paid posts. The composition form concerns selection by wealth under equal recognition and differential participation by network position under the conditions of Proposition 1. The participation results are most likely where substitution is strong and funding grows slowly; network sorting also requires the stated conditions on recognition and the career cutoffs.

United States data show that competition for paid posts was already intense before the machine (Fig. 5). The number of research doctorates awarded each year rose from fewer than 9,000 in 1958 to 58,131 in 2024 (National Center for Science and Engineering Statistics 2026). Among science, engineering and health doctorate holders employed in academia, the share holding full-time faculty posts fell from 87.5 per cent in 1973 to 70.5 per cent in 2019 (National Science Board 2021). The same imbalance appears in research funding. Applications for NIH R01-equivalent grants nearly doubled between 1998 and 2024, while the number of awards rose by 13 per cent. The success rate therefore fell from 31 to 19 per cent (National Institutes of Health 2026).

These series do not measure the weak form. Doctorates awarded are an inflow, not the stock of people trained to research standard; the faculty share is conditional on academic employment and separates faculty posts from other paid posts, not paid work from unpaid work; and neither measures output or the sectoral shift described above, since a doctorate holder who moves to industry leaves both the numerator and the denominator of the faculty share. The series instead describe the market that the machine enters. They predate the machine and show that paid posts were already scarce relative to doctorates when artificial intelligence arrived.

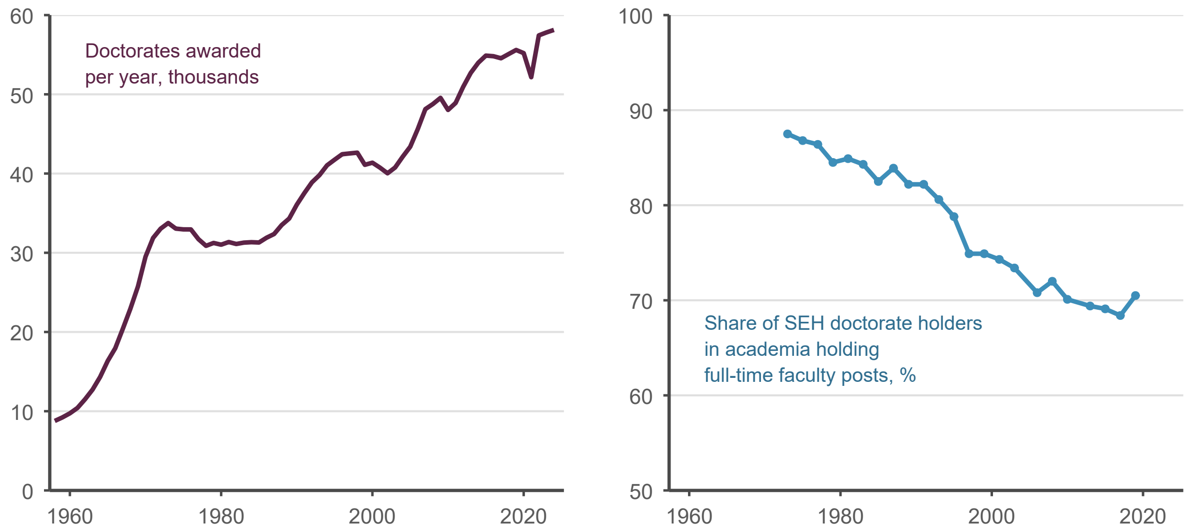

Fig. 5 Doctorates and faculty posts in the United States. Left: research doctorates awarded, 1958–2024 (National Center for Science and Engineering Statistics 2026). Right: share of academically employed science, engineering and health doctorate holders in full-time faculty posts, 1973–2019 (National Science Board 2021).

The studies of artificial intelligence reviewed above are consistent with some of the model's early pressures. Establishing whether the full mechanism is at work requires measuring capability, paid employment and recognition together.

These measurements also point to choices for funders and research institutions. Budget growth η_B helps determine whether wider capability supports more paid careers. Funders who count rising output as success while budgets remain flat may miss growing pressure on those careers. Access cost κ matters for who can use the new capability and who can afford to stay in research. Subsidised access can therefore ease a specific financial barrier. How institutions deploy artificial intelligence also matters for σ: they can use it to assist human judgement or to replace tasks. Evaluation practices can likewise influence ρ, the extent to which abundant output strengthens the advantage of professional connections. Evaluation can rely less on signals that track connection, such as journal prestige and referee eminence, and more on direct assessment of the work. Blind and algorithm-assisted review can support such assessment. A research system suited to the machine age would measure who can still afford to enter the profession and whether credit follows the work rather than the network.

A profession that requires private wealth and inherited connection selects its members by advantage as well as ability. It excludes capable people because they cannot afford to enter or because their work is not recognised. In the model they go on producing, so what is lost is not their work but their place in the profession that funds, certifies and reads it. The same technology that makes more people able to do science can restrict the ability to do it for a living, and to receive credit for it, to people who could already afford the work and were already known. A research system that measures output alone will not record that loss.

6 Conclusion

Does artificial intelligence democratise science? Yes, it makes the ability to do science more widely available, but the pay and credit that turn science into a career are separate outcomes. The model states the conditions under which they become less widely available. When machines substitute for human research labour, the budget does not keep pace and recognition is held equal and constant, more people can produce research while fewer can earn a living from it, and those who remain are disproportionately wealthy. When abundant output makes the profession rely more heavily on reputation, recognition shifts towards the well-connected relative to the poorly connected as the capable population grows. These outcomes are not contradictory. They are two effects of the same mechanism.

The paper challenges the assumption that more people able to do research must mean a larger paid profession. The two have come apart before. The gentlemen of science were capable and unpaid; the professionalisation of the nineteenth century joined capability to a salary and a credential; the chess engine made strong analysis widely available without determining how many paid careers that capability could support. The machine age can reverse the professionalisation episode, and an evaluation system that counts output will record the larger producing population as success while the contraction of the profession goes unmeasured.

It is the researchers paid closest to subsistence and holding the least private wealth who feel this first (in practice, those on fixed-term posts and at the periphery), and it is most likely in fields where the machine substitutes for human research labour and budgets grow too slowly to offset the displacement. Complements exist. Motion-sensing research after Kinect and citizen astronomy show that automation and wider participation can support research activity. Their implications for paid employment require separate evidence. Where corporate budgets fund frontier research, a third outcome is possible: a shift in the sectoral composition of paid research, which university indicators alone would record as a loss. The path a field follows depends not only on the machine but also on choices that institutions can influence: the growth of the research budget, whether the machine is used to replace or to assist human judgement, the cost of access and whether credit is allocated by the work or by the network.

Those four quantities can be measured field by field. Following task exposure, substitution and real funding over time, alongside the wealth and connections of researchers who remain in paid posts, would help test where capability and careers are moving apart. Charles Darwin never earned a salary for doing science. The machine age may produce many more scientists without salaries. Whether they will be paid and credited for doing science is the question that the machine leaves unanswered.

A The model

This appendix sets out the assumptions, equations and proofs behind the results in the text.

A person i has innate skill $s_i \in [0,1]$ with distribution F_s, wealth W_i with distribution F_W and network position $N_i > 0$. Machine capability is a. Access to the machine costs a flow $\kappa(a)$, and wealth earns a return $r > 0$. Effective skill is $q_i = s_i + x_i\, g(a)(1 - s_i)$, where access is $x_i \in \{0,1\}$, $g' > 0$ and $0 < g < 1$. Production requires $q_i \geq \bar{q}$. The least-skilled person who reaches the threshold with the machine has $s_c(a) = (\bar{q} - g)/(1 - g)$, which falls as a rises. Let $G(a) = F_s(\bar{q}) - F_s(s_c)$ denote the mass newly made capable; it is positive and increasing in the interior range, defined by $\bar{q} < 1$, $g(a) < \bar{q}$ and $f_s > 0$ on $(s_c, \bar{q})$. Access is affordable when $W_i \geq W_A(a) = \kappa/r$. With $\bar{F}_W = 1 - F_W$ and $s \perp W$, the capable mass is $C = C_0 + G\,\bar{F}_W(W_A)$, where C_0 is the incumbent mass. Writing the wealth hazard as $h_W = f_W/\bar{F}_W$,

$$C'(a) > 0 \iff \frac{G'}{G} > h_W(W_A)\,\frac{\kappa'}{r}. \tag{C}$$

When $\kappa' < 0$, capability always expands.

Research services combine human labour L and machine services Z with elasticity of substitution σ. The machine price m falls at rate $\tau > 0$. The budget is $B(a)$ with growth rate η_B. Let h be the human cost share and $w > 0$ the cash wage. Human labour demand is $L^d = Bh/w$, and the share responds to prices according to $\mathrm{d}\log h = (1-\sigma)(1-h)(\mathrm{d}\log w - \mathrm{d}\log m)$. Differentiating in logs with $\mathrm{d}\log m = -\tau\,\mathrm{d}a$ gives

$$\frac{\mathrm{d}\log L^d}{\mathrm{d}a} = \eta_B - (\sigma - 1)(1-h)\tau - \varepsilon_D\,\frac{w'}{w}, \qquad \varepsilon_D = \sigma + (1-\sigma)h > 0. \tag{R1}$$

Capability q_i does not appear in (R1).

Research provides pleasure $H(a)$, with $H' > 0$, and attributable meaning $M(a) = v - \delta(a)$, with $M' < 0$, where δ is the output that would have been produced without the researcher. Person i values these amenities at $A_i = \theta_{H,i}H + \theta_{M,i}M$, with non-negative taste weights. Amenities enter the want-to condition below. Each paid post supplies one unit of labour and receives salary w, which is also the price of a unit of labour. There is no intensive margin: $\ell \equiv 1$ and $\varepsilon_I = 0$. Labour supply is therefore $L^s = P_T$, so

$$\frac{\mathrm{d}\log L^s}{\mathrm{d}a} = \frac{P_T'}{P_T}. \tag{R2}$$

A fixed pool $\Pi > 0$ of recognition, measured in the consumption-equivalent units below, is divided among all capable people, the set counted in C, each of whom is assumed to produce research whether or not a budget pays her. A capable person i receives

$$b_i(a) = \Pi\,\frac{N_i^{\lambda(a)}}{\sum_{j\ \text{capable}} N_j^{\lambda(a)}}, \qquad \lambda(a) = \lambda_0 e^{\rho a}, \quad \lambda_0 > 0, \tag{Ncap}$$

and a person who is not capable receives $b_i = 0$. If all capable people have the same network position, each receives Π/C. Network capital enters the allocation of recognition, not capability or labour demand directly. Recognition can affect the equilibrium wage through participation.

Units are as in the main text: a post is full time, supplies one unit of labour and pays w, so every term below is measured as income, or its consumption equivalent, per period; b_i is monetised recognition net of w and B; and every participant pays κ. Participation requires $w+b_i+rW_i \geq \underline{c}+\kappa$, which defines the cutoff

$$W_{P,i}(a) = \frac{\underline{c} + \kappa(a) - w(a) - b_i(a)}{r}. \tag{A.1}$$

The want-to condition is $u_i = w + b_i - \kappa + A_i \geq \bar{u}$, where $\bar{u}$ is the value of the outside option and A_i the person's own amenity value; it is assumed slack for anyone who can afford the career, so amenities belong to this margin and not to the affordability margin that determines P_T. When recognition is equal across people and constant, $b_i = \bar{b}$ is absorbed into the consumption floor and set to zero, giving the wealth-only cutoff $W_P = (\underline{c} + \kappa - w)/r$. If incumbents and the newly capable draw wealth from the same distribution, total paid participation is, using $W_P > W_A$ so that the career cutoff subsumes the access cutoff,

$$P_T(a) = (C_0 + G(a))\, \bar{F}_W(W_P(a)), \qquad \frac{P_T'}{P_T} = \frac{G'}{C_0 + G} - h_W(W_P)\,\frac{\kappa' - w'}{r}. \tag{P3}$$

Equating (R1) with (R2), substituting (P3) under equal and constant recognition, and collecting the terms in w' on the positive coefficient $\varepsilon_D/w + h_W(W_P)/r$ gives

$$w' = \frac{\eta_B - (\sigma - 1)(1 - h)\tau - \dfrac{G'}{C_0 + G} + h_W(W_P)\,\dfrac{\kappa'}{r}}{\dfrac{\varepsilon_D}{w} + \dfrac{h_W(W_P)}{r}}. \tag{R3}$$

With fixed input per post and the want-to margin slack, amenities do not change the wage. The final term in the denominator is the participation feedback, which reduces the pass-through of every force in the numerator.

Theorem 1 (The capability–participation wedge)**.** *Suppose that the wealth distribution has a positive continuous density and both cutoffs are in the interior of its support. Suppose also that skill and wealth are independent; incumbents and the newly capable draw wealth from the same distribution; every participant pays the access cost κ; the career cutoff exceeds the access cutoff; recognition is equal across people and constant; the wage w is positive; and the want-to condition is slack for those with a sustainable career. Then artificial intelligence expands capability ($C' > 0$) while reducing total paid participation ($P_T' < 0$) and raising the career cutoff ($W_P' > 0$) if and only if*

$$h_W(W_A)\,\frac{\kappa'}{r} \;<\; \frac{G'}{G} \qquad \text{and} \qquad \frac{G'}{C_0 + G} \;<\; h_W(W_P)\,\frac{\kappa' - w'}{r}, \tag{F}$$

where w' is the equilibrium response in (R3)*. Let $d = \varepsilon_D/w$. Substituting* (R3)*, the second condition* *is equivalent to the form that does not contain w':*

$$\frac{G'}{C_0 + G} \; < \; \frac{h_W(W_P)}{r} \cdot \frac{d\,\kappa' + (\sigma - 1)(1-h)\tau - \eta_B}{d}. \tag{F$'$}$$

Proof. The first inequality is (C). The second is $P_T' < 0$ in (P3); since $G'/(C_0 + G) \geq 0$, it forces $\kappa' - w' > 0$, which is $W_P' > 0$. Substituting (R3) into it and dividing by the positive factor $1 - (h_W/r)/(\varepsilon_D/w + h_W/r)$ gives (F$'$); the direction of the inequality is preserved. □

Theorem 1 holds recognition constant. If instead the pool is divided equally among the capable, $b = \Pi/C$ and $b' = -\Pi C'/C^2 < 0$ when $C' > 0$. The cutoff is then $W_P = (\underline{c} + \kappa - w - b)/r$, the term $h_W \kappa'/r$ in the numerator of (R3) becomes $h_W(\kappa' - b')/r$, and the contraction condition becomes $G'/(C_0 + G) < h_W(\kappa' - b' - w')/r$. Comparing the two local responses at the same baseline wage, cutoff and recognition level, $\kappa' - b' - w'$ exceeds its constant-recognition value by $-b'\,d/D_{\text{eq}} > 0$, where $D_{\text{eq}} = d + h_W/r$ is the denominator of (R3). At that common baseline, contraction is therefore at least as easy, and the conditions of Theorem 1 are sufficient rather than necessary. This is a local comparison; it does not order equilibria with different baseline recognition levels.

Because $G'/(C_0 + G) < G'/G$, total paid participation contracts under a less demanding condition than paid participation among the newly capable alone, $P(a) = G\,\bar{F}_W(W_P)$. Let R denote the right-hand side of (F$'$). Contraction is feasible only when $R > 0$. A capability growth rate that satisfies both conditions in (F) exists exactly when $\max\{0, G\,h_W(W_A)\kappa'/r\} < (C_0 + G)\,R$; when $\kappa' \leq 0$ this reduces to $R > 0$.

Proposition 1 (Compounding selection)**.** *Let $\rho > 0$ and $\lambda_0 > 0$, and hold the pool Π fixed. Recognition rises with own network position, $\partial \log b_i/\partial \log N_i = \lambda(1 - s_i) > 0$ where $s_i = b_i/\Pi$, so the cutoff* (A.1) *falls with it. Three further results follow from* (Ncap)*. First, consider any two types with $N_H > N_L$ that are capable at both capability levels compared. Their relative recognition is $b_H/b_L = (N_H/N_L)^{\lambda(a)}$, which rises with a regardless of changes elsewhere in the capable set. Over a discrete rise from a_0 to a_1, with $\Delta\lambda = \lambda(a_1) - \lambda(a_0) > 0$ and $Z(a) = \sum_{j \text{ capable}} N_j^{\lambda(a)}$, a type capable at both levels has $b_i(a_1)/b_i(a_0) = (N_i/N_*)^{\Delta\lambda}$ with $N_* = [Z(a_1)/Z(a_0)]^{1/\Delta\lambda}$, so absolute recognition rises for $N_i > N_*$ and falls for $N_i < N_*$. Second, hold the capable set fixed and let $s_j = b_j/\Pi$ denote recognition shares. An individual's share rises if and only if $\log N_i$ exceeds the recognition-weighted mean $\sum_j s_j \log N_j$. Third, recognition enters the cutoff* (A.1) *negatively. Let ΔT denote the common change in $(\underline{c} + \kappa - w)/r$ between two capability levels and $\Delta b_H > \Delta b_L$ the changes in recognition of a high- and a low-network type. If $\Delta b_L/r < \Delta T < \Delta b_H/r$, the cutoff of the high type falls while that of the low type rises. Holding each type's capable population and wealth distribution fixed, participation weakly increases for the high type and weakly decreases for the low type, strictly when positive mass crosses the respective cutoffs. The effect on the wealth distribution of participants requires further restrictions. Positive regression dependence of wealth on network position alone does not establish that effect: a lower cutoff can admit poorer members of the high-network type. These results are not imposed in Theorem 1, which holds recognition equal, and do not determine the sign of P_T'.*

Proof. With weights $z_i = N_i^{\lambda}$, differentiating (Ncap) at a fixed capable set gives $\mathrm{d}\log b_i/\mathrm{d}a = \lambda'[\log N_i - \sum_j s_j \log N_j]$, where $\lambda' = \rho\lambda > 0$. The pairwise ratio $b_H/b_L = (N_H/N_L)^{\lambda}$ follows because the denominator cancels, and the finite-change identity follows from $b_i(a_1)/b_i(a_0) = N_i^{\Delta\lambda} Z(a_0)/Z(a_1)$. The third statement follows from (A.1): $W_{P,i}$ changes by $\Delta T - \Delta b_i/r$. For a fixed capable population of a type, lowering its cutoff weakly expands its participant set and raising it weakly contracts that set. □

Data availability

The replication file reproduces every condition in the model numerically and every figure from the parameters stated in the text. The United States series in Fig. 5 are drawn from published National Science Foundation and National Science Board reports cited in the text. All files will be deposited in a public repository on acceptance.

References

Ahmed, Nur, Muntasir Wahed, and Neil C. Thompson. 2023. "The Growing Influence of Industry in AI Research." *Science*, 379(6635): 884–886.

Alberts, Bruce, Marc W. Kirschner, Shirley Tilghman, and Harold Varmus. 2014. "Rescuing US Biomedical Research from Its Systemic Flaws." *Proceedings of the National Academy of Sciences*, 111(16): 5773–5777.

arXiv. 2026. "arXiv Monthly Submission Statistics." https://arxiv.org/stats/monthly_submissions, Accessed 18 August 2026.

Athey, Susan, and Michael Luca. 2019. "Economists (and Economics) in Tech Companies." *Journal of Economic Perspectives*, 33(1): 209–230.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279–1333.

Azagra-Caro, Joaquín M., and Ana M. Tur-Porcar. 2026. "Scientific Impact at the Expense of Happiness? Work/Life Balance in Performance-Driven Research Careers." *Research Evaluation*, 35: rvag030.

Bianchini, Stefano, Moritz Müller, and Pierre Pelletier. 2022. "Artificial Intelligence in Science: An Emerging General Method of Invention." *Research Policy*, 51(10): 104604.

Bourdieu, Pierre. 1975. "The Specificity of the Scientific Field and the Social Conditions of the Progress of Reason." *Social Science Information*, 14(6): 19–47.

Brynjolfsson, Erik, Bharat Chandar, and Ruyu Chen. 2025. "Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence." Stanford Digital Economy Lab Working Paper.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2025. "Generative AI at Work." *Quarterly Journal of Economics*, 140(2): 889–942.

Card, David, and Stefano DellaVigna. 2013. "Nine Facts about Top Journals in Economics." *Journal of Economic Literature*, 51(1): 144–161.

Cassar, Lea, and Stephan Meier. 2018. "Nonmonetary Incentives and the Implications of Work as a Source of Meaning." *Journal of Economic Perspectives*, 32(3): 215–238.

Cockburn, Iain M., Rebecca Henderson, and Scott Stern. 2019. "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis." In *The Economics of Artificial Intelligence: An Agenda.* , ed. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 115–146. Chicago:University of Chicago Press.

Colussi, Tommaso. 2018. "Social Ties in Academia: A Friend Is a Treasure." *The Review of Economics and Statistics*, 100(1): 45–50.

Daniels, George H. 1967. "The Process of Professionalization in American Science: The Emergent Period, 1820–1860." *Isis*, 58(2): 150–166.

Doshi, Anil R., and Oliver P. Hauser. 2024. "Generative AI Enhances Individual Creativity but Reduces the Collective Diversity of Novel Content." *Science Advances*, 10(28): eadn5290.

Fochler, Maximilian, Ulrike Felt, and Ruth Müller. 2016. "Unsustainable Growth, Hyper-Competition, and Worth in Life Science Research: Narrowing Evaluative Repertoires in Doctoral and Postdoctoral Scientists' Work and Lives." *Minerva*, 54(2): 175–200.

Fourie, Johan. 2026*a*. "The Price of Submission." Working paper, Stellenbosch University. `https://johanfourie.com/files/wp/JF_ThePriceOf_v1.pdf`.

Fourie, Johan. 2026*b*. "The Value of Peer Review and the Reward to Reputation." Working paper, Stellenbosch University. `https://johanfourie.com/files/wp/JF_ValueOfPeer_v5.pdf`.

Furman, Jeffrey L., and Florenta Teodoridis. 2020. "Automation, Research Technology, and Researchers' Trajectories: Evidence from Computer Science and Electrical Engineering." *Organization Science*, 31(2): 330–354.

Gaessler, Fabian, and Henning Piezunka. 2023. "Training with AI: Evidence from Chess Computers." *Strategic Management Journal*, 44(11): 2724–2750.

Gans, Joshua S. 2026. "Replaceable but Employed: Automation and the Meaning of Work." National Bureau of Economic Research NBER Working Paper 35559.

Hicks, Diana, Paul Wouters, Ludo Waltman, Sarah de Rijcke, and Ismael Rafols. 2015. "Bibliometrics: The Leiden Manifesto for Research Metrics." *Nature*, 520(7548): 429–431.

Hui, Xiang, Oren Reshef, and Luofeng Zhou. 2024. "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market." *Organization Science*, 35(6): 1977–1989.

Humlum, Anders, and Emilie Vestergaard. 2025. "Large Language Models, Small Labor Market Effects." National Bureau of Economic Research NBER Working Paper 33777.

International Chess Federation. 2024. "FIDE World Championship Game 11: Ding Collapses under Pressure as Gukesh Takes the Lead." https://www.fide.com/fide-world-championship-game-11-ding-collapses-under-pressure-as-gukesh-takes-the-lead/, 8 December.

International Correspondence Chess Federation. 2025. "World Championship 33 Final." https://www.iccf.com/event?id=100104, Final crosstable. Accessed 5 September 2026.

Lankford, John. 1981. "Amateurs and Astrophysics: A Neglected Aspect in the Development of a Scientific Specialty." *Social Studies of Science*, 11(3): 275–303.

Larson, Richard C., Navid Ghaffarzadegan, and Yi Xue. 2014. "Too Many PhD Graduates or Too Few Academic Job Openings: The Basic Reproductive Number R0 in Academia." *Systems Research and Behavioral Science*, 31(6): 745–750.

Latour, Bruno, and Steve Woolgar. 1986. *Laboratory Life: The Construction of Scientific Facts.* . 2nd ed., Princeton, NJ:Princeton University Press.

Lazear, Edward P., and Sherwin Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy*, 89(5): 841–864.

Lucier, Paul. 2009. "The Professional and the Scientist in Nineteenth-Century America." *Isis*, 100(4): 699–732.

Marshall, Philip J., Chris J. Lintott, and Leigh N. Fletcher. 2015. "Ideas for Citizen Science in Astronomy." *Annual Review of Astronomy and Astrophysics*, 53: 247–278.

Merton, Robert K. 1968. "The Matthew Effect in Science." *Science*, 159(3810): 56–63.

Morgan, Allison C., Nicholas LaBerge, Daniel B. Larremore, Mirta Galesic, Jennie E. Brand, and Aaron Clauset. 2022. "Socioeconomic Roots of Academic Faculty." *Nature Human Behaviour*, 6(12): 1625–1633.

Morrell, Jack, and Arnold Thackray. 1981. *Gentlemen of Science: Early Years of the British Association for the Advancement of Science.* Oxford:Clarendon Press.

Nästesjö, Jonatan. 2025. "Between Delivery and Luck: Projectification of Academic Careers and Conflicting Notions of Worth at the Postdoc Level." *Minerva*, 63(1): 69–92.

National Center for Science and Engineering Statistics. 2026. "Doctorate Recipients from U.S. Universities: 2024." National Science Foundation, NSF 26-315, Alexandria, VA.

National Institutes of Health. 2026. "NIH Data Book: R01-Equivalent Grants—Competing Applications, Awards, and Success Rates." https://report.nih.gov/nihdatabook, Accessed 18 August 2026.

National Science Board. 2021. "Science and Engineering Indicators 2022: The STEM Labor Force of Today." National Science Foundation, NSB-2021-2, Alexandria, VA.

Noy, Shakked, and Whitney Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science*, 381(6654): 187–192.

Polanyi, Michael. 1962. "The Republic of Science: Its Political and Economic Theory." *Minerva*, 1(1): 54–73.

Ranjit, Jaspreet, Ke Zhou, Swabha Swayamdipta, and Daniele Quercia. 2026. "Are We Automating the Joy Out of Work? Designing AI to Augment Work, Not Meaning."

Rosen, Sherwin. 1981. "The Economics of Superstars." *American Economic Review*, 71(5): 845–858.

Rothenberg, Marc. 1981. "Organization and Control: Professionals and Amateurs in American Astronomy, 1899–1918." *Social Studies of Science*, 11(3): 305–325.

Royal Society. n.d.*a*. "History of the Royal Society." https://royalsociety.org/about-us/who-we-are/history/, Accessed 5 September 2026.

Royal Society. n.d.*b*. "Hooke, Robert (1635–1703): Biographical Record." https://catalogues.royalsociety.org/CalmView/Record.aspx?id=NA8242&src=CalmView.Persons, Accessed 5 September 2026.

Sauermann, Henry, and Michael Roach. 2014. "Not All Scientists Pay to Be Scientists: PhDs' Preferences for Publishing in Industrial Employment." *Research Policy*, 43(1): 32–47.

Shapin, Steven. 1989. "The Invisible Technician." *American Scientist*, 77(6): 554–563.

Shapin, Steven. 2008. *The Scientific Life: A Moral History of a Late Modern Vocation.* Chicago:University of Chicago Press.

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations.* London:W. Strahan and T. Cadell.

Stephan, Paula E. 2012. *How Economics Shapes Science.* Cambridge, MA:Harvard University Press.

Stern, Scott. 2004. "Do Scientists Pay to Be Scientists?" *Management Science*, 50(6): 835–853.

United States Chess Federation. n.d.. "Glossary." *https://www.uschess.org/index.php?id=7327&option=com_content&task=view*, Entry on adjournments. Accessed 5 September 2026.

Wilsdon, James, Liz Allen, Eleonora Belfiore, Philip Campbell, Stephen Curry, Steven Hill, Richard Jones, Roger Kain, Simon Kerridge, Mike Thelwall, Jane Tinkler, Ian Viney, Paul Wouters, Jude Hill, and Ben Johnson. 2015. "The Metric Tide: Report of the Independent Review of the Role of Metrics in Research Assessment and Management." Higher Education Funding Council for England.