April 28, 2025

Miika Päällysaho

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Ph.D. awarded: October 17, 2024 (Stockholm University)

Current research activity:

My current research focuses on two broad topics within labor, public, and health economics.

1. First, I study how social insurance programs affect the health and healthcare use of benefit recipients. This work contributes to a recent and growing literature that highlights the broader effects of social insurance and income transfer programs beyond those on e.g., labor supply or consumption (see e.g., Gelber et al. 2023 and the review by Page 2024). Understanding whether social insurance programs improve beneficiaries' health is intrinsically important, but it also matters since changes in health can affect healthcare use. As healthcare is highly subsidized in most developed economies, any effects on healthcare use can create large fiscal externalities – a possibility that existing studies have overlooked.

   In two ongoing projects, we study the effects of social insurance programs on health and healthcare use with Swedish register data, focusing on the contexts of unemployment insurance (Nekoei et al. 2025a) and disability insurance (Nekoei et al. 2025b). To obtain exogenous variation in benefit levels, in both projects we use non-linearities in the benefit schemes created by benefit floors and caps in a regression kink design.

   Preliminary findings indicate that, especially in the context of DI, more generous benefits reduce the total costs of beneficiaries' healthcare use and even their mortality rate (as in Gelber et al. 2023). Moreover, for DI recipients the positive fiscal externalities created by falling healthcare costs are larger than the negative externalities due to labor supply distortions, which the existing literature has focused on (see Hendren & Sprung-Keyser 2020, Gelber et al. 2017, and references therein).

2. Second, I have three ongoing projects related to the determinants of the demand and supply of multidimensional human capital. In a recent published article (Hermo et al. 2022, attached), we argue using data on Swedish men that changes in the labor market returns to logical reasoning relative to vocabulary knowledge can explain a meaningful share (a third) of the increase in measured logical reasoning skills observed across birth cohorts.

   In a single-authored project (Päällysaho 2025), I extend our previous work using Finnish data. These data are unique as they allow measuring trends in cognitive skills *as well as* personality traits across birth cohorts for the near population of Finnish men (cf. Jokela et al. 2017). I develop and estimate a general equilibrium model of the demand and supply of cognitive skills and personality traits. My goal is to use the estimated model to (i) analyze the counterfactual evolution of both skill dimensions had their labor market returns remained unchanged or had technological change in the labor market remained skill neutral, and (ii) compare the estimated labor market returns to skills when allowing vs. not allowing for skill supply to endogenously adjust to changes in labor market returns.

   In a second project (Päällysaho et al. 2025), we use the Finnish data to study spatial variation in cognitive skills and personality traits across places. We document strong and sizable positive correlations between the log population of municipalities and their average skill levels. Using a mover design and a structural model, we then decompose these relationships into a component reflecting the causal effect of place on skills, a component reflecting spatial sorting based on skills by parents, and a component reflecting spatial sorting based on skills by children in adulthood.

   In a third project (Kuhakoski et al. 2025), we study whether changes over time in students' cognitive endurance (ability to sustain performance in cognitively demanding tasks, cf. Brown et al. 2024) can help explain the decline in scores on the PISA test observed in developed countries. Our analysis exploits the fact that test content and the order of test items are partly randomized across students.

April 28, 2025

Contribution to Summer Institute's research community and expected gains from attending:

My ongoing projects on the broader effects of social insurance and on the demand and supply of multidimensional human capital align closely with the themes featured at the Summer Institute. I would be excited to contribute to discussions by highlighting how Nordic register data can be used to push the research frontier on these questions. I would also bring a distinctive perspective to the Summer Institute's research community, shaped by my experience working with Nordic register data and by being part of a research community that has been underrepresented at the conference. Although Finnish register data offers similarly rich opportunities for economic research, researchers based in Finland—and those using Finnish data—have had significantly less visibility at the conference than their Nordic counterparts.

Attending the Summer Institute would also be personally meaningful. It would give me the chance to learn directly from scholars whose work has shaped my thinking, and to connect with researchers working on similar questions in different contexts. I would especially be looking forward to exchanging ideas, getting feedback on ongoing projects, and exploring collaborations that could continue beyond the conference. For an early-career researcher like me, these interactions would be invaluable both for my current work and for shaping the direction of my research going forward. I also believe that the connections I could build at the conference would benefit my colleagues in Finland and at my alma mater (Stockholm University) as well.

Summer Institute 2025 sessions most interested in attending:

- NBER SI 2025 Labor Studies (July 21-23, 2025)
- NBER SI 2025 Public Economics (July 22-23, 2025)
- NBER SI 2025 Economics of Social Security (July 23, 2025)
- NBER SI 2025 Economics of Health (July 23-24, 2025)

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Kuhakoski, J., Päällysaho, M., & Uusitalo, R. (2025). "Decomposing Trends in the PISA Study." Research in progress.

Nekoei, A., Päällysaho, M., & Seim, D. (2025a). "Unemployment Insurance Generosity and Health: Evidence from Sweden." Working paper, Stockholm University.

Nekoei, A., Päällysaho, M., Seim, D., & Wikström, J. (2025b). "Disability Insurance and Health: Evidence and Implications." Research in progress.

Page, M. E. (2024). "New Advances on an Old Question: Does Money Matter for Children's Outcomes?" Journal of Economic Literature 62 (3): 891–947. https://doi.org/10.1257/jel.20231553.

Päällysaho, M. (2025). "Multidimensional Skills in General Equilibrium: Theory and Evidence." Research in progress.

Päällysaho, M., Silliman, M., & Warnes, P. (2025). "The Polarization of Skills Across Space and Time." Research in progress.

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Miika Matias Päällysaho

Basic Information

Date of Birth: December 20, 1992
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Positions

Senior Researcher, *VATT Institute for Economic Research*, September 2024 – present

Education

Ph.D. in Economics, Department of Economics, *Stockholm University*, October 2024
Price Theory Summer Camp, Becker Friedman Institute, *University of Chicago*, June 2023
Master of Social Sciences, Faculty of Social Sciences, *University of Helsinki*, July 2017
Bachelor of Social Sciences, Faculty of Social Sciences, *University of Helsinki*, September 2015

Professional Experience

September 2024 – present, Senior Researcher, *VATT Institute for Economic Research*
June – November 2020, Research Assistant for Professors David Seim and Jesse Shapiro
January 2020 – October 2021, Research Assistant for Professors David Seim and Arash Nekoei
December 2018 – February 2019, Research Assistant for Professor Arash Nekoei
August 2017 – August 2018, Research Assistant, *The Research Institute of the Finnish Economy (ETLA)*
May – August 2017, Research Trainee, *Labour Institute for Economic Research (Labore)*
May – August 2016, Research Trainee *VATT Institute for Economic Research*

Publications

(1) "Essays in Labor, Public, and Health Economics", Dissertations in Economics 2024:4. Stockholm, Sweden: Department of Economics, Stockholm University, September 2024
(2) "Labor Market Returns and the Evolution of Cognitive Skills: Theory and Evidence" (with Santiago Hermo, David Seim, and Jesse Shapiro), *The Quarterly Journal of Economics* 137(4): 2309–2361, November 2022

Work in Progress

"Multidimensional Skills in General Equilibrium: Theory and Evidence" (single-authored)
"The Polarization of Skills Across Space and Time" (with Mikko Silliman and Pablo Warnes)
"Decomposing Trends in the PISA Study" (with Jani Kuhakoski and Roope Uusitalo)
"Disability Insurance and Health: Evidence and Implications" (with Arash Nekoei, David Seim, and Jens Wikström)
"Unemployment Insurance Generosity and Health: Evidence from Sweden" (with Arash Nekoei and David Seim)
"Adoption of Medical Innovations Across Hospitals and Socioeconomic Groups: Evidence from Sweden" (with Fabian Sinn)
"Family-Level Stress and Children's Educational Choice: Evidence from Parent Layoffs" (with Julia Tanndal)

Other Work

(1) "Työvoimapalvelujen vaikuttavuus taloustieteellisessä tutkimuskirjallisuudessa", Report commissioned by the National Audit Office of Finland, June 2020

(2) "Palkkatuen vaikuttavuus – palkkatukijärjestelmän ja sen uudistuksien arviointi" (with Rita Asplund, Antti Kauhanen, and Pekka Vanhala), Publications of the Government's analysis, assessment and research activities 75/2018, December 2018

(3) "The Short- and Long-Term Effects of Graduating During a Recession: Evidence from Finland", VATT Working Papers 96, VATT Institute for Economic Research: Helsinki, Finland, October 2017

(4) "The Short- and Long-Term Effects of Graduating During a Recession: Evidence from Finland", Master's Thesis, University of Helsinki, May 2017

Grants, Scholarships, and Awards

Grant (24,000 EUR) for research project "Psychological Traits, Decision-Making, and the Labor Market" (co-PI with Ramin Izadi, Toni Juuti, Martti Kaila, and Mikko Silliman), *Yrjö Jahnsson Foundation*, December 2024

Hedelius Scholarship (declined), *Jan Wallanders och Tom Hedelius stiftelse*, December 2019

Faculty of Social Sciences Prize, Best Master's thesis in Economics at the University of Helsinki, December 2017

Seminars

2024: VATT Institute for Economic Research

2023: *Labor Fika* seminar, Stockholm University

2022: *Labor Fika* seminar (×2), Stockholm University

2020: Brown Bag seminar, Stockholm University

2021: Brown Bag seminar, Stockholm University

2018: The Research Institute of the Finnish Economy (ETLA)

2017: Labour Institute for Economic Research

Referee Service

Academic journals: *Journal of Labor Economics (×1)*, *Journal of Public Economics (×1)*

Teaching Experience

EC7410 – Econometrics 1 (Master level, Stockholm University), TA for Peter Skogman Thoursie, Fall 2021

EC7411 – Econometrics 2 (Master level, Stockholm University), TA for Per Pettersson Lidbom, Spring 2020 & 2021

Languages and Software

Languages: Finnish (native), English (fluent), Swedish (good), Spanish (basics), French (basics)

Software: Stata, R, Python, LaTeX, git, Adobe InDesign

Other Information

Co-organizer of the *Labor Fika* seminar series at Stockholm University, September 2021 – June 2023

Editor, *Kapitaali* magazine, KTTO ry, University of Helsinki, January – December 2014

Mandatory Finnish military service, Karjalan Prikaati, Vekaranjärvi, July 2012 – March 2013

August 2008 – June 2011, General upper secondary education (*lukio*), *Helsingin yliopiston Viikin normaalikoulu*

Studies in music theory and classical guitar, *Itä-Helsingin musiikkiopisto*, August 2001 – May 2010

References

Professor **David Seim**, Stockholm University, Department of Economics, david.seim@su.se

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LABOR MARKET RETURNS AND THE EVOLUTION OF COGNITIVE SKILLS: THEORY AND EVIDENCE*

SANTIAGO HERMO
MIIKA PÄÄLLYSAHO
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JESSE M. SHAPIRO

A large literature in cognitive science studies the puzzling "Flynn effect" of rising fluid intelligence (reasoning skill) in rich countries. We develop an economic model in which a cohort's mix of skills is determined by different skills' relative returns in the labor market and by the technology for producing skills. We estimate the model using administrative data from Sweden. Combining data from exams taken at military enlistment with earnings records from the tax register, we document an increase in the relative labor market return to logical reasoning skill as compared to vocabulary knowledge. The estimated model implies that changes in labor market returns explain 37% of the measured increase in reasoning skill, and can also explain the decline in knowledge. An original survey of parents, an analysis of trends in school curricula, and an analysis of occupational characteristics show evidence of increasing emphasis on reasoning as compared to knowledge. *JEL Codes:* J24, J31, O52.

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I. Introduction

A large and important literature in cognitive science documents substantial gains in intelligence (IQ) scores across successive cohorts in developed countries, sometimes called the "Flynn effect" (see, for example, Schaie, Willis, and Pennak 2005; Flynn 2007, 2012; Trahan et al. 2014; Pietschnig and Voracek 2015; Flynn and Shayer 2018).[1] These gains are especially pronounced for *fluid intelligence*, a notion of general reasoning ability often measured with abstract reasoning tasks (Pietschnig and Voracek 2015). There are less pronounced gains, or even declines, in *crystallized intelligence*, a notion of domain knowledge often measured with knowledge assessments such as vocabulary tests (Schaie, Willis, and Pennak 2005; Pietschnig and Voracek 2015).[2] Understanding the causes of these trends is important in part because of evidence that a population's level of cognitive skills influences its economic productivity, economic growth, and distribution of income (e.g., Bishop 1989; Hanushek and Woessmann 2008, Section 5).[3]

There is no consensus on the precise causes of cohort trends in cognitive performance, which some consider to be an important puzzle.[4] Research in cognitive science emphasizes factors, such as improvements in health and nutrition, that expand the supply of skill (e.g., Pietschnig and Voracek 2015; Rindermann, Becker, and Coyle 2017). But the incentive to invest in particular dimensions of skill may also evolve over time in response to the demands of the economy.

In this article, we study the role of labor market returns in determining cohort trends in skill levels and skill composition. We focus on Sweden, where an administrative data join between standardized test scores (collected for military conscription

1. Rindermann, Becker, and Coyle (2017) write, "Among the most discussed topics in intelligence research is the rise of average IQ test results across generations in the 20th century" (242).

2. Cattell (1943) writes, "Fluid ability has the character of a purely general ability to discriminate and perceive relations between any fundaments, new or old... Crystallized ability consists of discriminatory habits long established in a particular field" (178).

3. There is also evidence that a population's level of cognitive skills is related to its levels of patience and risk aversion (Falk et al. 2018; Potrafke 2019).

4. Deary (2020) writes, "If there were a prize in the field of human intelligence research, it might be for the person who can explain the 'Flynn effect'" (also quoted in Wai and Putallaz 2011).

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typically at age 18 or 19) and earnings (collected by the tax agency over the life cycle) allows us to measure the level of and return to skill in a consistent way across cohorts for the near population of men.

We develop a model of an economy whose aggregate output is determined by the aggregate skills of workers. Skills, which can be multidimensional, are determined by an exogenous endowment (e.g., health) and an investment decision made early in life (by parents, children, and schools). The investment decision is in turn influenced by the lifetime labor market returns to different skills. We identify the relative returns to different skills by assuming that unobserved determinants of an individual's earnings are correlated with the individual's skill endowment only through its market value. Under this assumption, the relative returns to different skills can be recovered from a Mincerian regression of the log of earnings on skills in a cross section of individuals.

We parameterize the model so that a single unknown parameter governs the degree to which individuals can substitute investment across skill dimensions. We identify this parameter by assuming that long-run average shocks to the technology for producing skills are proportional across fluid and crystallized intelligence.

We take the model to the data. Across the birth cohorts 1962–1975, we find that performance on a logical reasoning task—our proxy for fluid intelligence—improved by 4.4 percentile points, measured in terms of the distribution in the 1967 cohort. The estimated lifetime earnings premium to an additional percentile point of logical reasoning performance fell by 0.08 log points, from a base of 0.48 log points. Turning to performance on a vocabulary knowledge test—our proxy for crystallized intelligence—we find that performance declined by 2.9 percentile points. The estimated lifetime premium to an additional percentile point of vocabulary knowledge fell by 0.07 log points, but from a much lower base of 0.16 log points.

Because logical reasoning performance rose while its market return fell, a model in which logical reasoning is the only skill dimension would imply that there must have been an increase in the supply of skill, consistent with the hypothesis of a growth in the endowment of fluid intelligence of the sort emphasized in the cognitive science literature. A richer picture emerges when incorporating the second skill dimension. Vocabulary knowledge

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performance fell along with its market return, suggesting a decline in the demand for this skill dimension. Moreover, the premium to vocabulary knowledge relative to logical reasoning fell by 38 log points. Seen through the lens of our model, the declining relative premium to crystallized intelligence drove a reallocation of effort toward developing abstract reasoning and away from acquiring knowledge.

We use the model to decompose the observed trends in skills into a portion driven by changing labor market returns and a portion driven by other factors. According to the estimated model, if the market returns to different skills had remained constant at their 1962 level, logical reasoning and vocabulary knowledge performance would have increased by 2.8 and 3.0 percentile points, respectively. The estimated model thus implies that trends in labor market returns explain 37% of the growth in logical reasoning performance (roughly, $100 \times \frac{4.4-2.8}{4.4}$) and more than fully explain the decline in vocabulary knowledge.

We extend our baseline analysis in a few directions. First, we use a nationally representative survey linked to earnings records to expand our analysis to a broader set of birth cohorts, from 1948 to 1977, and to skills measured at a younger age, around age 13. We find that the relative level of and return to logical reasoning performance rose across these cohorts, although our estimates are less precise than those from the (much larger) enlistment sample. Second, we adjust the estimated trends in skill levels and skill returns to account for the role of covariates such as height and secondary school completion. Although adjusting for covariates is conceptually delicate, as some covariates may respond to labor market returns, we find broadly similar conclusions across a variety of sensitivity analyses. Third, we extend our model to incorporate noncognitive skills. We estimate a smaller, but still important, role for changes in labor market returns in explaining the evolution of cognitive skills, and we highlight limitations of the analysis that arise because the measure of noncognitive skills in our data is not directly comparable across cohorts.

We also explore whether the main actors in skill investment—parents and schools—place increasing emphasis on reasoning relative to knowledge. In an original survey, we find that parents of more recent cohorts tend to regard reasoning ability as more important for their children than knowledge of facts. In a review of pedagogical scholarship, and an original

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quantitative text analysis, we find evidence of a trend toward increasing emphasis on reasoning relative to knowledge in primary school curricula in Sweden. Turning to the demand for skills, we show evidence of relative growth in occupations that place more emphasis on reasoning as opposed to knowledge. We view this evidence as consistent with the mechanism underlying our estimated model.

Our analysis has some important limitations. A first limitation is that we treat the skill demand portion of the model fairly abstractly and do not offer a precise account of why some skills have become relatively more valuable in the labor market over time, though we show some suggestive evidence based on occupational characteristics. A second limitation is that our conclusions require assumptions on unmeasured determinants of earnings and skills. We specify and discuss these assumptions, their plausibility, and their importance in more detail in the body of the article, where we also discuss evidence on sensitivity to departures from key assumptions. A third limitation is that we focus on the labor market returns to skills and do not measure their nonmarket returns, though we show that our conclusions are preserved if market and nonmarket returns to skill move in proportion across cohorts. A final limitation is that, due to the nature of the military enlistment data, our main analyses are limited to men only, though in the Online Appendix we show results for women in the survey sample.

The main contribution of this study is to develop and apply an economic model to quantify the role of labor market returns in determining cohort trends in multidimensional cognitive skills. We are not aware of prior work that does this. A large literature in economics studies the determinants and market value of (possibly multidimensional) cognitive and noncognitive skills (see, for example, the review by Sanders and Taber 2012 and recent papers by Roys and Taber 2020; Agostinelli and Wiswall 2020). Our analysis of the market for skills is closely related to the work of Katz and Murphy (1992) and the large literature that follows (see Deming 2017 and the review by Acemoglu and Autor 2011), but differs in focusing on explaining trends across cohorts (rather than time periods) and in offering an explicit quantitative model of the supply of (rather than demand for) skills. As we do, Heckman, Lochner, and Taber (1998) develop a general equilibrium model of the supply and demand for skill. Their model is richer than ours in its treatment of

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labor demand but does not incorporate multiple dimensions of skill.[5]

A large literature in cognitive science (reviewed, for example, in Pietschnig and Voracek 2015) studies causes of trends in various measures of ability or intelligence. Although some work in this literature considers the possibility that social demands affect the development of skills, we are not aware of work in this literature that quantifies trends in the economic returns to different types of skills or that uses an estimated model to link trends in skills to trends in their returns.[6] We are also not aware of prior work that quantifies long-term trends in parents' and schools' emphasis on reasoning versus knowledge.[7]

An additional contribution of this article is to document trends in the relative labor market returns to different dimensions of cognitive skill. Much prior work in economics and other fields studies trends in the level of and returns to skills,[8] including some work using linked administrative data from elsewhere in Europe,[9] as well as some work using the same data from Sweden

5. Our model of the supply of skill, which focuses on cohort-level trends, is more stylized than work that focuses on the skill formation process itself (see Cunha et al. 2006; Cunha, Heckman, and Schennach 2010; Doepke, Sorrenti, and Zilibotti 2019). In particular, unlike much of the work reviewed in, say, Heckman and Mosso (2014), we treat the skill investment decision as static and do not model the dynamics of skill formation during childhood.

6. Dickens and Flynn (2001) specify and simulate a quantitative model in which genetic endowments and environmental factors interact to produce measured intelligence. They discuss the role of occupational demands in driving cohort differences in skills, but do not incorporate labor market returns into their quantitative model and do not estimate the model's parameters. Flynn (2018, 79) notes that "When society asks us to increase our use of any skill over time, the brain responds," and cites research by Maguire, Woollett, and Spiers (2006) on the effect of occupational demands on brain structure in the context of London taxi and bus drivers.

7. Okagaki and Sternberg (1993) study group differences in parents' conceptions of intelligence. Bietenbeck (2014) studies the effects on reasoning and knowledge skills of traditional and modern teaching practices. Cunha, Elo, and Culhane (forthcoming), among others, study the relationship between parents' beliefs about the technology of skill formation and parents' investments in children's skills.

8. For example, Castex and Dechter (2014) use survey data to document falling returns to cognitive skills as measured by Armed Forces Qualification Test scores in the United States between the 1980s and 2000s.

9. For example, Jokela et al. (2017) document cohort trends in personality traits using scores from military conscripts in Finland, and argue based on estimated labor market returns that the economic significance of cohort trends in personality traits is similar to that of cohort trends in cognitive abilities.

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that we use.[10] Rönnlund et al. (2013) report trends in test scores in Sweden from 1970 to 1993. Lindqvist and Vestman (2011) study the labor market return to cognitive and noncognitive skills in Sweden. Especially related, Edin et al. (2022) estimate trends in the returns to cognitive and noncognitive skills in Sweden. None of these papers document trends in the relative lifetime labor market returns to different dimensions of cognitive skill or quantify the role of labor market returns in driving cohort trends in skill levels in a model with multidimensional skills.[11]

The remainder of the article is organized as follows. Section II presents our model and approach to identification. Section III describes the data we use. Section IV presents our main findings. Section V discusses additional evidence related to the mechanisms in the model. Section VI extends our analysis to incorporate noncognitive skills. Section VII concludes.

II. Model

II.A. Production and Earnings

There is a finite population of workers $i \in \mathcal{N}$, each of which is associated with a cohort $c(i) \in \{\underline{c}, \ldots, \bar{c}\}$. Each worker is characterized by a skill level $\mathbf{x}_i \in \mathbb{R}^J_{\geqslant 0}$ for $J \geqslant 2$.

In each time period t, each worker i has an experience level $a(i, t) = t - c(i)$ and supplies efficiency units $z_{it} \in \mathbb{R}_{\geqslant 0}$, where $z_{it} > 0$ if $a(i, t) \in \{1, \ldots, A\}$ and $z_{it} = 0$ otherwise. Thus, members of cohort c enter the labor force in period $c + 1$ and exit the labor force after period $c + A$, and we identify the cohort c with the period immediately before workers in the cohort enter the labor force.

Let $\mathbf{X}_t$ be the $J \times A$ matrix whose ath column is given by the sum of $z_{it}\mathbf{x}_i$ over all workers i with experience level $a(i, t) = a$.

Markussen and Røed (2020, Section 4.2) document declining labor market returns to men's cognitive skills using test scores from enrollment in military service in Norway.

10. These data have also been used to study, among other topics, the effect of schooling on measured skills (Carlsson et al. 2015) and the effect of officer training on occupational outcomes later in life (Grönqvist and Lindqvist 2016).

11. Jokela et al. (2017) document trends in the within-cohort rank correlation between three different dimensions of cognitive skill and earnings at age 30 (Figure 2, panel B) or ages 30–34 (Figure S1, panel B), but do not report trends in lifetime labor market returns from a model of earnings that accounts for multiple skill dimensions simultaneously. Lindquist (2005) models trends in the demand for skill in Sweden arising from capital-skill complementarity.

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This matrix collects the total supply of skill in period t for each dimension j and experience level a. Let $\mathbf{X}_t^{-i}$ be the analogue of $\mathbf{X}_t$ excluding worker i.[12]

Total output Y_t at time t is given by

$$Y_t = F_t(\mathbf{X}_t),$$

where $F_t(\cdot)$ is a scalar-valued differentiable function that may vary over time, for example due to changes in production technology.

In each period t, a worker i earns his marginal product w_{it}, which is given by

$$\begin{aligned} w_{it} &= F_t(\mathbf{X}_t) - F_t\left(\mathbf{X}_t^{-i}\right) \\ &\approx z_{it} \nabla F'_{t,a(i,t)} \mathbf{x}_i, \end{aligned}$$

where $\nabla F_{t,a}$ is the gradient of $F_t(\mathbf{X}_t)$ at $\mathbf{X}_t$ with respect to the ath column of $\mathbf{X}_t$. We assume that $\nabla F'_{t,a(i,t)} \mathbf{x}_i > 0$ for all workers i in all periods t of working life. Motivated by a large-population setting, we treat $\mathbf{X}_t$ as fixed from the perspective of any individual worker i.

Pick a period t of worker i's working life, so that $z_{it} > 0$, and rewrite the earnings equation as

$$\ln(w_{it}) \approx \ln(z_{it}) + \ln\left(\nabla F'_{t,a(i,t)} \mathbf{x}_i\right).$$

Now take a first-order approximation around the mean skill level $\mathbf{x}_{t,a\left(i,t\right)}$ of individuals who share worker i's experience level at time t to get

$$\ln(w_{it}) \approx \ln(z_{it}) + \ln\left(\nabla F'_{t,a(i,t)} \mathbf{x}_{t,a(i,t)}\right) + \frac{\nabla F'_{t,a(i,t)}}{\nabla F'_{t,a(i,t)} \mathbf{x}_{t,a(i,t)}} \left(\mathbf{x}_i - \mathbf{x}_{t,a(i,t)}\right),$$

where we will again treat $\mathbf{x}_{t,a\left(i,t\right)}$ as fixed from the perspective of any individual worker i. We can write the preceding as

$$\ln(w_{it}) \approx B_{t,a(i,t)} + \mathbf{p}'_{t,a(i,t)} \mathbf{x}_i + \ln(z_{it}), \tag{1}$$

12. That is, the ath column of $\mathbf{X}_t$ is

$$\sum_{\{l \in \mathcal{N}:\ a(l,t)=a\}} z_{lt} \mathbf{x}_l,$$

and that of $\mathbf{X}_t^{-i}$ is

$$\sum_{\{l \in \mathcal{N} \setminus \{i\}:\ a(l,t)=a\}} z_{lt} \mathbf{x}_l.$$

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where $B_{t,a}$ is a scalar, $\mathbf{p}_{t,a}$ is a vector of skill premia, and both are specific to a time period and experience level.[13]

We proceed taking equation (1) to be exact. Although we have derived equation (1) from a particular model of the labor market, any model in which earnings take the form in equation (1) will be equivalent for the purposes of our subsequent analysis. Moreover, although for concreteness we refer to z_{it} as efficiency units, equation (1) makes clear that z_{it} captures any individual-and-period-specific determinants of earnings that are not included in $\mathbf{x}_i$.

II.B. Skill Investment

At the beginning of life, each worker i chooses his skills $\mathbf{x}_i$ subject to the constraints

$$\begin{aligned} \mathbf{x}_i &\geqslant \mu_i \\ S_{c(i)}(\mathbf{x}_i - \mu_i) &\leqslant \overline{S}_{c(i)}, \end{aligned} \tag{2}$$

where $\mu_i \in \mathbb{R}^J$ is an individual skill endowment, $\overline{S}_c \in \mathbb{R}_{>0}$ is a cohort-specific skill budget, and $S_c(\cdot)$ is a cohort-specific transformation function.

We can think of $\mathbf{x}_i - \mu_i \in \mathbb{R}^J_{\geqslant 0}$ as the skill investment of individual i, that is, the increment in skills over and above the individual's endowment μ_i. The endowment μ_i represents cross-sectional differences in a cohort, say in ability or access to schooling. The budget $\overline{S}_c$ can be seen as representing the total time and effort available for skill investment. The transformation function $S_c(\cdot)$ may be thought of as governing the ease of skill investment and of substituting investment across skill dimensions. The budget $\overline{S}_c$ and the function $S_c(\cdot)$ may differ across cohorts because of trends in the technology of skill formation, say, because of improvements in health or nutrition. Although for simplicity we refer to the decision maker as the worker, we may alternatively think of the skill investment decision as being made by the worker's parents, or by a collective decision-making process involving the worker, his parents, and the schooling system.[14] Because we take the timing

13. Specifically,

$$B_{t,a} = \ln\left(\nabla F'_{t,a}\mathbf{x}_{t,a}\right) - 1, \qquad \mathbf{p}_{t,a} = \frac{\nabla F_{t,a}}{\nabla F'_{t,a}\mathbf{x}_{t,a}}.$$

14. For example, we may think of the skill budget $\overline{S}_c$ as reflecting the sum of the effective time and effort available from the worker, his parents, and his teachers.

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of entry into the labor market as given, we do not account for any forgone earnings due to time spent acquiring skills.

Each worker consumes his earnings in each period and has time-separable preferences with a felicity function given by the log of consumption. Each worker discounts future felicity by a discount factor $\delta \in (0, 1]$. At the time of choosing the skill investment, worker i has full knowledge of the path of skill premia over his life cycle, $\{\mathbf{p}_{c(i)+a,a}\}_{a=1}^{A}$. We further assume that worker i's skill investment does not influence the path of z_{it}.

It follows that the worker's problem is equivalent to maximizing $\mathbf{P}_{c(i)}'\mathbf{x}_i$ subject to expression (2), where

$$\mathbf{P}_{c(i)} = \frac{\sum_{a=1}^{A} \delta^a \mathbf{p}_{c(i)+a,a}}{\sum_{a=1}^{A} \delta^a} \tag{3}$$

is the net present value of the skill premia $\mathbf{p}_{c(i)+a,a}$ at different experience levels a, normalized by the constant $\sum_{a=1}^{A} \delta^a$ to have a convenient interpretation as a weighted average. We refer to $\mathbf{P}_c$ as the *lifetime skill premia* faced by cohort c. Although we have assumed for concreteness that workers have full knowledge of the path of skill premia, the linearity of equation (1) in $\mathbf{x}_i$ means that we can alternatively allow for uncertainty in skill premia by replacing $\mathbf{p}_{c(i)+a,a}$ in equation (3) with its expectation.[15] Likewise, although we have assumed that skills $\mathbf{x}_i$ are fixed throughout working life, it is possible to accommodate a linear, deterministic evolution of skills over the lifetime under a suitable reinterpretation of $\mathbf{p}_{c(i)+a,a}$ in equation (3).[16]

The worker's problem is also equivalent to maximizing $\mathbf{P}_{c(i)}'\tilde{\mathbf{x}}_i$ subject to $\tilde{\mathbf{x}}_i \geqslant 0$ and $S_{c(i)}(\tilde{\mathbf{x}}_i) \leqslant \overline{S}_{c(i)}$, where $\tilde{\mathbf{x}}_i = \mathbf{x}_i - \mu_i$. The solutions to this problem depend only on the cohort $c(i)$ of

15. That is, taking $\mathrm{E}_c[\cdot]$ to be an expectation with respect to the information set of workers in cohort c at the time that skill investments are made, we can take the worker's expected discounted utility to be

$$\frac{\sum_{a=1}^{A} \delta^a \mathrm{E}_{c(i)}\left[\mathbf{p}_{c(i)+a,a}'\right]}{\sum_{a=1}^{A} \delta^a}\mathbf{x}_i.$$

16. Specifically, suppose that each worker enters working life with chosen skills $\mathbf{x}_{i,0} = \mathbf{x}_i$, which then evolve with experience according to $\mathbf{x}_{i,a} - \mathbf{x}_{i,a-1} = \Lambda_{c(i),a}\mathbf{x}_{i,a-1}$ for $a \in \{1, \ldots, A\}$, with $\Lambda_{c,a} > -I_J$ elementwise for all c, a. Then we can take $\mathbf{p}_{c(i)+a,a}' = \tilde{\mathbf{p}}_{c(i)+a,a}' \prod_{a'=1}^{a}(\Lambda_{c(i),a'} + I_J)$ where $\tilde{\mathbf{p}}_{c(i)+a,a}$ are the (contemporaneous) premia to the worker's skills $\mathbf{x}_{i,a}$ at experience level a.

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the worker and not on the worker's identity. In this sense, within-cohort variation in skill levels arises only due to variation in the individual skill endowment μ_i. We assume that μ_i has mean zero within each cohort. This assumption is without loss of generality because we can always define $\mathbf{x}_i$ and μ_i relative to a cohort-specific mean endowment.[17]

II.C. Parameterization and Identification

We assume that the transformation function $S_c(\cdot)$ takes the constant elasticity form

$$S_c(\tilde{\mathbf{x}}) = \left(\sum_{j=1}^{J} K_{cj}^{\rho-1} \tilde{x}_j^{\rho} \right)^{\frac{1}{\rho}}, \tag{4}$$

where $\mathbf{K}_c \in \mathbb{R}^J_{>0}$ is a vector-valued parameter that we may think of as describing the cost of increasing skill along each of the J dimensions for cohort c, and $\rho > 1$ is a scalar parameter that determines the substitutability of effort across different skill dimensions.

Worker i's problem has a unique solution, with $\tilde{\mathbf{x}}_i = \tilde{\mathbf{x}}_{i'}$ if $c(i) = c(i')$. Therefore write $\tilde{\mathbf{x}}_c = \tilde{\mathbf{x}}_c(\mathbf{P}_c)$ as the optimal $\tilde{\mathbf{x}}_i$ for all workers i in cohort c. Here $\tilde{\mathbf{x}}_c(\cdot)$ is a *skill supply function* that returns the optimal skill investment for members of cohort c given the lifetime skill premia $\mathbf{P}_c$.[18] We assume that $\mathbf{P}_c > 0$ for all c.

Imagine an econometrician who has data $\{(\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\overline{c}}$ and wishes to learn the skill supply function $\tilde{\mathbf{x}}_c(\cdot)$. Focus on the first two dimensions, where we may think of fluid intelligence as dimension $j = 1$ and crystallized intelligence as dimension $j = 2$.

17. To see this, start with an endowment $\mathring{\mu}_i$ with mean $\mathring{\mu}_c = \frac{\sum_{\{i:c(i)=c\}} \mathring{\mu}_i}{|\{i:c(i)=c\}|}$ in cohort c, where $\mathring{\mu}_c$ need not be zero. The problem of maximizing $\mathbf{P}'_{c(i)} \mathring{\mathbf{x}}_i$ subject to $\mathring{\mathbf{x}}_i \geqslant \mathring{\mu}_i$ and $S_{c(i)}(\mathring{\mathbf{x}}_i - \mathring{\mu}_i) \leqslant \overline{S}_{c(i)}$ is equivalent to the problem of maximizing $\mathbf{P}'_{c(i)} \mathbf{x}_i$ subject to expression (2) where $\mathbf{x}_i = \mathring{\mathbf{x}}_i - \mathring{\mu}_{c(i)}$ and $\mu_i = \mathring{\mu}_i - \mathring{\mu}_{c(i)}$. Here μ_i has mean zero within each cohort by construction.

18. Specifically, for each skill $j \in \{1, \ldots, J\}$, we have

$$\tilde{x}_{cj}(\mathbf{P}_c) = \frac{P_{cj}^{\frac{1}{\rho-1}} K_{cj}^{-1}}{\left(\sum_{j'=1}^{J} P_{cj'}^{\frac{\rho}{\rho-1}} K_{cj'}^{-1} \right)^{\frac{1}{\rho}}} \overline{S}_c.$$

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Under the model, the relative supply of fluid intelligence obeys

$$\ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{c2}}\right) = \frac{1}{\rho - 1}\ln\left(\frac{P_{c1}}{P_{c2}}\right) - \ln\left(\frac{K_{c1}}{K_{c2}}\right). \tag{5}$$

A standard difficulty in learning the elasticity of substitution $\frac{1}{\rho-1}$ is that the unobserved costs $\mathbf{K}_c$ may affect both skill investments (via the workers' incentives) and skill premia (via the labor market). We assume that, on average, there is no trend in the relative costs of the two skill dimensions.

ASSUMPTION 1 (Zero average relative supply shock). We assume that

$$\frac{1}{\bar{c} - \underline{c}}\sum_{c=\underline{c}}^{\bar{c}-1}\left[\ln\left(\frac{K_{c+1,1}}{K_{c+1,2}}\right) - \ln\left(\frac{K_{c1}}{K_{c2}}\right)\right] = 0.$$

Under Assumption 1, long-run improvements in the technology for producing skills are not systematically biased toward either fluid or crystallized intelligence.

Assumption 1 is sufficient for the identification of $\tilde{\mathbf{x}}_c(\cdot)$ under a regularity condition on $\mathbf{P}_c$.

PROPOSITION 1. Under Assumption 1, if $\frac{P_{\underline{c}1}}{P_{\underline{c}2}} \neq \frac{P_{\bar{c}1}}{P_{\bar{c}2}}$, then the skill supply function $\tilde{\mathbf{x}}_c(\cdot)$ for each cohort c is identified from data $\{(\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\bar{c}}$.

All proofs are in Appendix A. The proof of Proposition 1 is constructive. Under Assumption 1, an explicit expression for ρ can be derived using equation (5). We can then learn the costs $\mathbf{K}_c$ and budget $\overline{S}_c$ up to suitable normalizations. The required regularity condition on $\mathbf{P}_c$ can in principle be checked in the data. Online Appendix A presents conditions for the identification of $\tilde{\mathbf{x}}_c(\cdot)$ in the presence of a social multiplier in skill investment in the spirit of Dickens and Flynn (2001, equation 2").

Proposition 1 requires that the econometrician knows $\mathbf{P}_c$. This requirement can be relaxed to require only that $\mathbf{P}_c$ is known up to scale.

COROLLARY 1. Under the conditions of Proposition 1, the skill supply function $\tilde{\mathbf{x}}_c(\cdot)$ for each cohort c is identified from data $\{(\alpha\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\bar{c}}$, where the scalar $\alpha > 0$ may be unknown.

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Corollary 1 allows the econometrician to understate or overstate the lifetime skill premia, provided the error is proportional across dimensions j and the constant of proportionality does not differ across cohorts. An immediate implication is that if there are nonmarket returns to skill that evolve in proportion to market returns—say, because skills earn a premium on the marriage market only to the extent they improve a person's earning potential—then measurement of market returns is sufficient for identification of the skill supply function.

What remains is to establish conditions for the identification of $\tilde{\mathbf{x}}_c$ and $\mathbf{P}_c$. Recall that we assume that μ_i has mean zero within each cohort, implying that $\tilde{\mathbf{x}}_c = \overline{\mathbf{x}}_c$ for $\overline{\mathbf{x}}_c$ the mean skill of individuals in cohort c. Identification of $\tilde{\mathbf{x}}_c$ from the distribution of $\mathbf{x}_i$ is therefore trivial.

Recall also that $\mathbf{P}_c$ is the net present value of cohort-and-period-specific skill premia $\mathbf{p}_{t,a} = \mathbf{p}_{t,t-c}$. We identify $\mathbf{p}_{t,t-c}$, up to scale, from a Mincerian regression of the log of earnings on measured skills. To do this, we restrict the relationship between the unobserved determinants of earnings z_{it} and skill endowments μ_i, allowing that the econometrician may also observe a vector of covariates $\mathbf{d}_{it}$.

ASSUMPTION 2. The values of z_{it} in each period t obey

$$\mathrm{E}(\ln(z_{it})|\mu_i = \mu,\ \mathbf{d}_{it} = \mathbf{d},\ c(i) = c) = \zeta_{t,t-c} + \tilde{\alpha}\mathbf{p}_{t,t-c}^{'}\mu + \mathbf{d}^{'}\beta_{t,t-c},$$

where $\zeta_{t,t-c}$ and $\beta_{t,t-c}$ are unknown parameters, and the scalar $\tilde{\alpha} \geqslant 0$ may also be unknown.

Assumption 2 allows that the unobserved determinants of earnings are linearly related to the observed covariates $\mathbf{d}_{it}$ and to the market value of the skill endowment $\mathbf{p}_{t,t-c}^{'}\mu_i$. Such a relationship can arise if the market supplies inputs complementary to the worker's endowment.[19]

19. Suppose, for example, that the efficiency units z_{it} of worker i at time t are given by $z_{it} = \tilde{z}_{it}\underline{z}_{t,a(i,t)}$, where $\tilde{z}_{it} \geqslant 1$ is the amount of some input and $\underline{z}_{t,a} = (\nabla F_{t,a}^{'}\mathbf{x}_{t,a})^{-1}$ is a scale factor that ensures that mean earnings in each period and experience level are unity if the minimum input is always supplied. Say that the input for worker i at time t is supplied competitively, with marginal product $\underline{z}_{t,a(i,t)}\nabla F_{t,a(i,t)}^{'}\mu_i$ given by the effect of an increase in $\tilde{z}_{it}$ on total output from the worker's skill endowment, and marginal cost $\tilde{\alpha}^{-1}(\ln(\tilde{z}_{it}) - \eta_{it})$ for η_{it} a shock. From equating marginal product and marginal cost, it follows that

$$\ln(\tilde{z}_{it}) = \tilde{\alpha}\mathbf{p}_{t,t-c}^{'}\mu_i + \eta_{it},$$

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Assumption 2 is sufficient to identify the cohort-and-period-specific skill premia $\mathbf{p}_{t,t-c}$, and hence the lifetime skill premia $\mathbf{P}_c$, up to scale, from the conditional expectation function of the log of earnings.

PROPOSITION 2. Under Assumption 2, for some scalar $\alpha > 0$, a multiple $\alpha\mathbf{P}_c$ of the lifetime skill premia for each cohort c is identified from the conditional expectation function of the log of earnings,

$$\mathrm{E}(\ln(w_{it})|\mathbf{x}_i = \mathbf{x},\ \mathbf{d}_{it} = \mathbf{d},\ c(i) = c),$$

for each time period $t \in \{c+1, \ldots, c+A\}$.

Importantly, Proposition 2 does not require that all determinants of earnings are observed, or that unobserved determinants of earnings are independent of skills. Instead, Proposition 2 requires that unobserved determinants of earnings are related to the skill endowment only through its market value, with a coefficient that does not vary across cohorts or periods. Online Appendix B presents alternative conditions for identification of $\mathbf{P}_c$ up to scale when skills are measured with error.

Although we identify $\mathbf{P}_c$ only up to an unknown multiple $\alpha > 0$, going forward we simply write as if $\alpha = 1$. Moreover, although for concreteness Assumption 2 requires that $\tilde{\alpha} \geqslant 0$, and hence that a regression of the log of earnings on skills will tend to overstate skill premia, the proofs of Corollary 1 and Proposition 2 make clear that $\tilde{\alpha} \neq -1$ is sufficient.

II.D. Discussion

Assumption 1 is violated if long-run improvements in skill production technology favor one skill dimension over the other. Testing this assumption is difficult because it imposes a restriction only on those changes in relative skill levels that would have occurred in the absence of changes in relative skill premia.[20]

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and therefore that Assumption 2 holds if

$$\mathrm{E}\left(\eta_{it}|\mu_i = \mu,\ \mathbf{d}_{it} = \mathbf{d},\ c\left(i\right) = c\right) = \tilde{\zeta}_{t,t-c} + \mathbf{d}^{'}\beta_{t,t-c}$$

in each period t for some $\tilde{\zeta}_{t,t-c}$.

20. Following the proof of Proposition 1, any data $\{(\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\bar{c}}$ such that $\mathbf{P}_c, \tilde{\mathbf{x}}_c > 0$ for all c, with $\mathrm{sgn}(\ln(\frac{\tilde{x}_{\bar{c}1}\tilde{x}_{\bar{c}2}}{\tilde{x}_{\bar{c}2}\tilde{x}_{\underline{c}1}})) = \mathrm{sgn}(\ln(\frac{P_{\bar{c}1}P_{\bar{c}2}}{P_{\bar{c}2}P_{\underline{c}1}})) \neq 0$, are compatible with our model and with Assumption 1.

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However, it is possible to obtain some clues about the plausibility of this assumption from prior research in cognitive science and economics. Improvements in schooling are one potentially important cause of changes in skill production technology. Pietschnig and Voracek (2015, Table 2) argue that higher levels of education are linked especially to greater crystallized intelligence.[21] Improvements in health and nutrition are another potentially important cause of changes in skill production technology. Pietschnig and Voracek (2015, Table 2) argue that some factors in this category (e.g., blood lead levels) do not affect fluid and crystallized intelligence differently, but that some (e.g., nutrition) have larger effects on fluid than crystallized intelligence.[22] Other changes that may have improved skill production technology include increased availability of personal technology (e.g., video games) and a reduction in disease burden (Pietschnig and Voracek 2015, Table 2).[23]

Thus there are factors that favor crystallized intelligence, factors that favor fluid intelligence, and factors that do not favor one or the other. We may think of Assumption 1 as describing a situation where the opposing factors wash out. To the extent that they do not, and that changes in skill production technology favor crystallized intelligence, we expect to understate the role of labor market returns in explaining trends in skills. To the extent that changes instead favor fluid intelligence, we expect to overstate the role of labor market returns.[24]

21. Cliffordson and Gustafsson (2008) and Carlsson et al. (2015) document stronger effects of schooling on crystallized than fluid intelligence using data from the same military enlistment battery that we study.

22. In a review of the literature, Lam and Lawlis (2017) identify randomized trials showing evidence of effects of micronutrient interventions on both fluid and crystallized intelligence, though with larger effect sizes for fluid intelligence. See also Lynn (2009, 253–54).

23. Pietschnig and Voracek (2015, 290–91) note that increased access to technology may have improved fluid more than crystallized intelligence, but also that gains in fluid intelligence have been observed in countries and time periods with lower levels of access to modern technology (see also Baker et al. 2015, 146). Simons et al. (2016) argue that there is limited evidence of effects of interventions such as video game playing on broader cognitive performance.

24. Say that $\frac{P_{\underline{c}1}}{P_{\underline{c}2}} > \frac{P_{\underline{c}1}}{P_{\underline{c}2}}$. If $\frac{1}{\bar{c}-\underline{c}}\sum_{c=\underline{c}}^{\bar{c}-1}[\ln(\frac{K_{c+1,1}}{K_{c+1,2}}) - \ln(\frac{K_{\underline{c}1}}{K_{\underline{c}2}})] > 0$, then our construction will understate the elasticity of substitution $\frac{1}{\rho-1}$. If $\frac{1}{\bar{c}-\underline{c}}\sum_{c=\underline{c}}^{\bar{c}-1}[\ln(\frac{K_{c+1,1}}{K_{c+1,2}}) - \ln(\frac{K_{\underline{c}1}}{K_{\underline{c}2}})] < 0$, then our construction will overstate it.

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In our empirical analysis, we explore the sensitivity of our findings to departures from Assumption 1 and to accounting for measurable changes in schooling and health occurring at or before the ages at which we measure skills. We also study skills measured at various ages and therefore at different points in a person's schooling.

Assumption 2 is violated if there are unmeasured factors that directly affect earnings and whose correlation with a person's skill endowment is not proportional to the endowment's market value. In our empirical analysis, we explore the sensitivity of our findings to including proxies for candidate factors in the covariate set $\mathbf{d}_{it}$.

III. Data

III.A. Linked Data on Test Scores and Earnings

Our main analysis uses data on scores from tests administered at military enlistment, typically at age 18 or 19, for the near population of Swedish men born between 1962 and 1975 and who enlisted between 1980 and 1993 (War Archives 2016). Across all cohorts, these men took identical tests that were part of a group of tests called Enlistment Battery 80. Carlstedt (2000), Rönnlund et al. (2013), and Gyllenram, Hellström, and Hanes (2015) describe the tests in more detail.

To extend our analysis to a broader set of birth cohorts and earlier testing ages, we use data on scores from tests administered, typically at age 13, as part of the Evaluation Through Follow-up, a large survey of Swedish families (Härnqvist 2000). These data cover around 10% of the birth cohorts 1948, 1953, 1967, 1972, and 1977. Härnqvist (1998) and Svensson (2011) describe the tests, which were unchanged across the cohorts, and the survey in more detail.[25] We focus on males to parallel the military enlistment sample. Online Appendix C presents supplementary findings for females.

Both data sources include tests for logical reasoning and vocabulary knowledge. In the enlistment data, the logical reasoning test consisted of drawing correct conclusions based on statements

25. Extensions of our analysis in Online Appendix C include data for birth cohorts 1982 and 1992, for which we can measure skill levels but have more limited information on earnings. The test administered to the 1982 and 1992 cohorts differs slightly from the test administered to earlier cohorts in aspects such as the order of possible answers.

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that are made complex by distracting negations or conditional clauses and numerical operations (Carlstedt and Mårdberg 1993; Gyllenram, Hellström, and Hanes 2015). The vocabulary knowledge test consisted of correctly identifying synonyms to a set of words (Gyllenram, Hellström, and Hanes 2015). In the survey data, the logical reasoning test consisted of guessing the next in a sequence of numbers, and the vocabulary knowledge test consisted of recognizing antonyms (Svensson 2011, Chapter 1). In both data sources, we observe the number of questions (out of a total of 40) that each person answered correctly on each test.[26]

We treat performance on the logical reasoning test as our main measure of fluid intelligence ($j = 1$). We treat performance on the vocabulary knowledge test as our main measure of crystallized intelligence ($j = 2$). Pietschnig and Voracek (2015, Table 1) list guessing the next number in a sequence as an example of a task that measures fluid intelligence and a vocabulary test as an example of a task that measures crystallized intelligence.[27]

Enlistees were assigned to military positions in part based on a composite cognitive score that depended on the logical reasoning test, the vocabulary knowledge test, and other tests (Grönqvist and Lindqvist 2016, 873–74, 877, 880). We are not aware of any incentives attached to the individual cognitive test components (e.g., logical reasoning, vocabulary knowledge), as opposed to the composite cognitive score, or any reason incentives to perform well on the tests would have differed by birth cohort. The test questions are classified and could not be practiced in advance, and the exact mapping from individual cognitive test components to the composite cognitive score was not publicly known at the time of the tests. We are not aware of any incentives attached to performance on the survey tests, which are not publicly available.

We include in our analysis only those individuals for whom we observe valid logical reasoning and vocabulary knowledge scores.

26. Both data sources include a test of spatial reasoning, which we use in sensitivity analysis. Online Appendix Figure 1 shows trends in the level of and premium for technical skills, which are measured in the military enlistment data but not in the survey data. Online Appendix Figure 2 shows trends in the levels of and premia for skills in the military enlistment data for men born between 1954 and 1961, for which the format of the tests was different (War Archives 2016).

27. Carroll (1993) lists induction and sequential reasoning as two of the three factors most frequently associated with fluid intelligence, and verbal ability as the factor most frequently associated with crystallized intelligence, in a tabulation based on a hierarchical factor analysis (598–99; see also Flanagan and Dixon 2014).

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For each data source and each dimension j, we let x_{ij} denote the percentile rank of individual i's score in the distribution of scores of those born in 1967.[28] The skill vector $\mathbf{x}_i = (x_{i1}, x_{i2})$ then measures the performance of individual i on each dimension j relative to the set of individuals born in 1967. Online Appendix Table 1 shows the number of individuals in each birth cohort for each data source.

We join both sources of test scores to information on labor market earnings for the universe of Swedish residents from the Income and Tax Register for the years 1968–2018.[29] For each individual i in each year t, we let w_{it} be the total gross labor market earnings.

Portions of our analysis use additional variables. From the enlistment data (War Archives 2016), we obtain the date on which an individual took the enlistment tests,[30] the individual's height and weight as of enlistment, and a measure of noncognitive skill that follows a standardized distribution.[31] From other sources we obtain administrative data on each individual's employment history (Statistics Sweden 2020, 2021), foreign-born status (Statistics Sweden 2014b), secondary schooling completion (Statistics Sweden 2014c), region of birth (Statistics Sweden 2021), family relations (Statistics Sweden 2014b), and parental labor market earnings (Statistics Sweden 2014a, 2021).

Appendix Table I presents sensitivity analyses with respect to many of the choices we have made in constructing the sample and variables for our analysis, including varying the set of included cohorts, measuring an individual's skill with the percent of the maximum possible score rather than with the percentile

28. Specifically, x_{ij} is equal to the average rank of sample individuals born in 1967 who have the same score as individual i on dimension j, multiplied by 100, divided by the number of sample individuals born in 1967, and centered by adding a constant so that x_{ij} has an average value of 50 among those born in 1967.

29. Data on labor market earnings for 1990–2018 are from Statistics Sweden (2021), where we define gross labor market earnings using the concept described in Statistics Sweden (2016a, 137–38). Data for 1968–1989 are from Statistics Sweden (2014a), where we approximate the concept described in Statistics Sweden (2016a, 137–38) using the available data fields. For sensitivity analysis, we also obtain data on business income for 1990–2018 from Statistics Sweden (2021). We define a total income measure combining labor market earnings and business income using the concept described in Statistics Sweden (2016a, 141–42).

30. We match information on enlistment test date to our other data using information on parish of residence from Statistics Sweden (2016b).

31. Noncognitive skill is evaluated based on an interview and scored on a Stanine (1–9) scale. Lindqvist and Vestman (2011, 107–9 and Appendix F) and Edin et al. (2022, 6) describe the measure in more detail.

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rank, combining logical and spatial reasoning skills into a single composite measure of fluid intelligence, and including business income in the measure of earnings. We summarize the quantitative implications of these choices in Section IV.B.

III.B. Original Survey of Parents' Perceptions

We conducted an original survey to assess the importance that parents place on different types of skills. We hosted the survey on a Stockholm University survey platform. We recruited participants via Facebook ads from October 17 through October 24, 2020. During this time, 1,199 respondents began the survey and 983 completed it. We asked each respondent their own year of birth as well as the range of birth years of their children, if any. We include in our analysis the 716 respondents who reported that their first child was born at least 16 years after their own birth year.

We asked these respondents the following question:

> As a parent, how much do you encourage (or did you encourage) your children to develop the qualities below while growing up?
>
> To be able to think critically and solve problems logically.
>
> To be able to remember facts, such as the definitions of difficult words.

We intended the first quality to approximate the concept of fluid intelligence and the second to approximate the concept of crystallized intelligence. We also asked respondents about the importance of each quality in today's society, how much their own parents emphasized each quality, and how much their own primary school emphasized each quality. There were five possible answers ranging from "not at all" to "very much," and we classified each response according to whether the person rated the first quality as more important, the second quality as more important, or neither.

Online Appendix Figure 3 gives screenshots of the consent form and survey form. Online Appendix Figure 4 shows the distribution of year of birth and year of birth of first child among the respondents in our sample.

IV. Results

IV.A. Trends in Skills and Skill Premia

We let $c(i)$ be the year that worker i turns 29 and we let $A = 26$, so that the working life is from ages 30 through 55.

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Online Appendix Figure 5 shows that full-time work tends to be highest during these years.

We estimate the parameter $\mathbf{p}_{t,a}$ in equation (1) by OLS regression of the log of labor market earnings $\ln(w_{it})$ on the vector of percentile ranks $\mathbf{x}_i$, separately for each worker experience level (age) a and for each year t for which we measure earnings, excluding men with zero earnings. This yields an estimate of $\mathbf{p}_{c+a,a}$ for each c, a such that $c + a \leqslant T$, for T the most recent year of earnings data available. Online Appendix Figure 6 illustrates the fit of the regression model for three example cohorts at three different ages.

To estimate $\mathbf{p}_{c+a,a}$ for c, a such that $c + a > T$, we take the average estimate for the given cohort c for all ages $a > 10$ for which a regression estimate of $\mathbf{p}_{c+a,a}$ is available. Online Appendix Figure 7 illustrates this extrapolation for three example cohorts.

We plug the resulting estimates of $\mathbf{p}_{c+a,a}$ into equation (3), along with the value $\delta = 0.96$, to get an estimate of the lifetime skill premia $\mathbf{P}_c$ for the cohorts $c \in \{\underline{c}, \ldots, \overline{c}\}$. We obtain standard errors for $\mathbf{P}_c$ via a nonparametric bootstrap in which we sample individuals i with replacement.

Figure I depicts the average skill levels $\overline{\mathbf{x}}_c$ and the estimated lifetime skill premia $\mathbf{P}_c$ across cohorts in the enlistment data along with their 95% pointwise confidence intervals and uniform confidence bands. For convenience we label cohorts with their birth year, that is, $c - 29$. Figure I also depicts the lines of best fit through the plotted series.

Figure I, Panel A shows that logical reasoning skill rose, on average, by 4.4 percentile points, relative to the 1967 distribution, across the birth cohorts from 1962 to 1975. By contrast, vocabulary knowledge skill fell, on average, by 2.9 percentile points. Online Appendix Figure 8 depicts the cumulative distribution functions of skills in the 1962 and 1975 cohorts. Online Appendix Figure 9 compares trends in skill in our data to those measured in other countries.

Figure I, Panel B shows that the lifetime skill premium fell for both logical reasoning and vocabulary knowledge. The line of best fit indicates that the lifetime premium for a percentile point of logical reasoning skill fell from 0.48 to 0.40 log points across the birth cohorts from 1962 to 1975, and the lifetime premium for a percentile point of vocabulary knowledge fell from 0.16 to 0.09 log points. Thus, the lifetime premium for both skill dimensions fell, with a proportionately much greater decline for vocabulary

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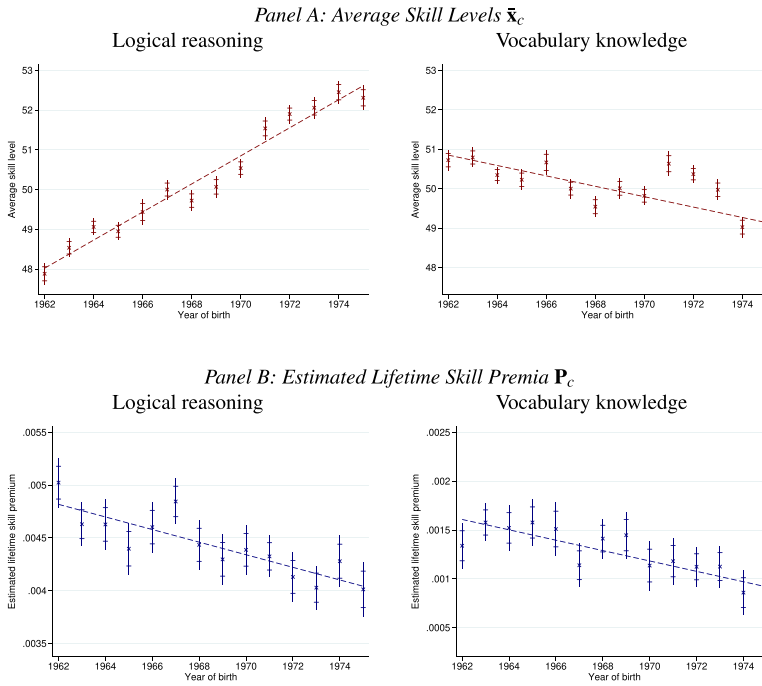


FIGURE I

Trends in Skills and Skill Premia across Birth Cohorts 1962–1975, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. Panel A depicts the average skill $\bar{\mathbf{x}}_c$ for each birth cohort c. Skills are expressed as a percentile of the distribution for the 1967 birth cohort. Panel B depicts the estimated lifetime skill premia $\mathbf{P}_c$ for each birth cohort, constructed as described in Section IV.A. Each plot depicts 95% pointwise confidence intervals (inner intervals, marked by dashes) and 95% uniform confidence bands (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

knowledge.[32] Online Appendix Figure 10 depicts estimated lifetime skill premia based on a generalization of equation (1) that allows interactions between the skill dimensions.

32. Prior work finding evidence of declining returns to cognitive skill includes Castex and Dechter (2014) for the United States, Markussen and Røed (2020) for Norway, and Edin et al. (2022) for Sweden.

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Figure II, Panel A depicts the evolution of the relative skill levels $\ln\left(\frac{\bar{x}_{c1}}{\bar{x}_{c2}}\right)$ and of the relative lifetime skill premia $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$ across the two dimensions. The plot shows that both objects tend to increase with later birth cohorts and are fairly close to the line of best fit, evoking a movement along a relative linear supply curve as in equation (5). Figure III shows that a similar qualitative pattern obtains in our survey sample, which is smaller and for which estimates tend to be less precise. Online Appendix Figure 11 depicts the underlying estimates of skill levels and lifetime skill premia for men in the survey sample. Online Appendix Figure 12 depicts the evolution of relative skill levels and relative lifetime skill premia for women in the survey sample. Online Appendix Figure 12 depicts the evolution of relative skill levels and relative lifetime skill premia in the enlistment sample by region of birth.

Under the conditions in Online Appendix B, our approach to identification and estimation of relative skill premia remains valid even in the presence of measurement error in skills. As an alternative exploration of the role of measurement error, requiring different assumptions from those in Online Appendix B, Online Appendix Table 2, Panel A shows estimates of the trend in skill premia computed using the individuals present in both the enlistment and survey data, instrumenting for skills measured at enlistment with skills measured in the survey. The sample is small, and the instrumental variables estimates are imprecise. The confidence intervals on the estimated trends include zero and also include the slope of the linear fit from Figure I, Panel B. Relative to the slope of the linear fit from Figure I, Panel B, instrumental variables estimates tend to show growth in the premium to logical reasoning and more rapid decline in the premium to vocabulary knowledge, suggesting even stronger trends in labor market incentives to invest in logical reasoning at the expense of vocabulary knowledge than in our baseline calculations. Online Appendix Table 2, Panel B reports small and statistically insignificant trends in the correlation between skills measured in the survey data and those measured in the enlistment data.

Appendix Table I presents sensitivity analyses with respect to many of the choices we have made in constructing the sample and variables for our analysis, including altering the assumed ages of working life, restricting to workers who are employed year-round in a typical year, averaging over a shorter or longer span of ages

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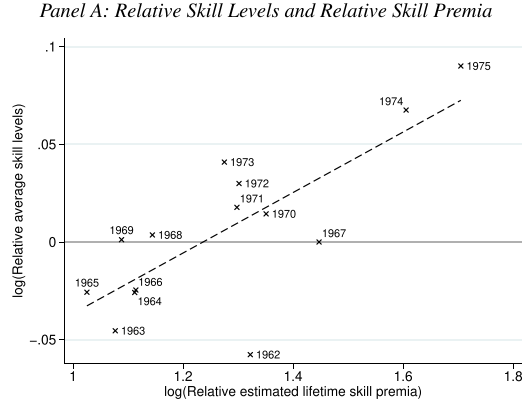


FIGURE II

Evolution of Relative Skill Levels and Relative Skill Premia, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. Panel A shows a scatterplot of the natural log of the relative average skill levels, $\ln\left(\frac{\bar{x}_{c1}}{\bar{x}_{c2}}\right)$, against the natural log of the relative estimated lifetime skill premia, $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$. The dashed line depicts the line of best fit. Panel B shows a scatterplot of the natural log of the relative average skill levels, $\ln\left(\frac{\bar{x}_{c1}}{\bar{x}_{c2}}\right)$, against the natural log of the relative estimated lifetime skill premia, $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$, based on the linearized skill premia depicted in Figure I, Panel B. The solid line shows the relative skill supply function estimated for the 1962 birth cohort, that is, the relationship between $\ln\left(\frac{\tilde{x}_{c,1}(\mathbf{P}_c)}{\tilde{x}_{c,2}(\mathbf{P}_c)}\right)$ and $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$. The slope of the solid line is equal to the estimated elasticity of substitution $\frac{1}{\rho-1}$. Panel C shows a scatterplot of the difference between average skill levels, $\bar{x}_{c1} - \bar{x}_{c2}$, against the difference between estimated lifetime skill premia, $P_{c1} - P_{c2}$, based on the linearized skill premia depicted in Figure I, Panel B. The ratio of the x-axis range to the x-axis value for the 1962 birth cohort is equal to the analogous ratio in Panel B.

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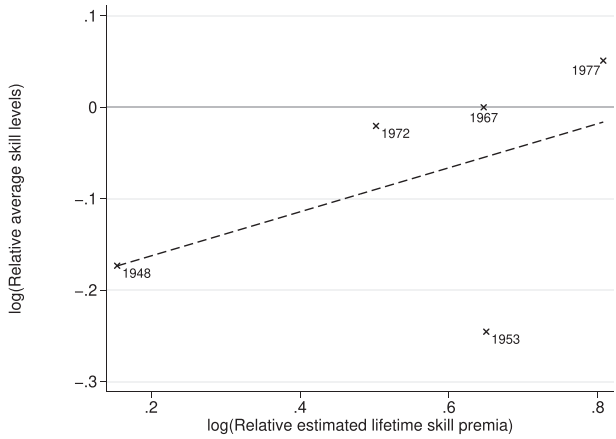


FIGURE III

Evolution of Relative Skill Levels and Relative Skill Premia, Survey Sample

Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, and 1977, with tests typically taken at age 13. The plot shows a scatterplot of the natural log of the relative average skill levels, $\ln\left(\frac{\bar{x}_{c1}}{\bar{x}_{c2}}\right)$, against the natural log of the relative estimated lifetime skill premia, $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$. The dashed line depicts the line of best fit.

to extrapolate premia to working years we do not observe in the data, and varying the assumed value of δ. We summarize the quantitative implications of these choices in Section IV.B.

IV.B. Model Estimates and Counterfactuals

We estimate the skill supply function $\tilde{\mathbf{x}}_c(\cdot)$ for each cohort in the enlistment sample following the construction in the proof of Proposition 1. We take $J = 2$. We take the average skill $\bar{\mathbf{x}}_c$ in each cohort as our estimate of $\tilde{\mathbf{x}}_c$. We take the linear fit in Figure I, Panel B as our estimate of the lifetime skill premia $\mathbf{P}_c$.[33] We may think of the linear fit either as a way of smoothing the sampling variation in the data or as a way of approximating the forward-looking expectations of workers at the time the skill investment decision is made. Table I, Panel A reports estimates of key parameters.

33. Consistent with the regularity condition in Proposition 1, based on the linear fit we reject the null hypothesis that $\ln(\frac{P_{\underline{c}1}}{P_{\underline{c}2}}) = \ln(\frac{P_{\bar{c}1}}{P_{\bar{c}2}})$ at conventional significance levels ($p = .0006$).

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TABLE I

SUMMARY OF DATA AND MODEL IMPLICATIONS

	Logical reasoning	Vocabulary knowledge
Panel A: Baseline		
Initial lifetime skill premium, 1962	0.0048	0.0016
$P_{\underline{c}j}$	(0.0001)	(0.0001)
Change in lifetime skill premium, 1962–1975	− 0.0008	− 0.0007
$P_{\bar{c}j} - P_{\underline{c}j}$	(0.0001)	(0.0001)
Initial average skill rank, 1962	47.88	50.72
$\tilde{x}_{\underline{c}j}$	(0.14)	(0.13)
Change in average skill rank 1962–1975	4.43	− 2.92
$\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}$	(0.22)	(0.21)
Under estimated model:		
Change in avg. skill rank, 1962–1975 at initial skill premia	2.80	2.97
$\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})$	(0.21)	(0.22)
Share of obs. change explained by change in skill premia	0.3681	2.0151
$1 - \frac{\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}}$	(0.0175)	(0.1483)
Substitution parameter	3.61	
ρ	(0.76)	
[Implied elasticity of substitution $\frac{1}{\rho-1}$]	[0.3830]	
Panel B: Accounting for noncognitive skills		
Initial lifetime skill premium, 1962	0.0037	0.0009
$P_{\underline{c}j}$	(0.0001)	(0.0001)
Change in lifetime skill premium, 1962–1975	− 0.0009	− 0.0006
$P_{\bar{c}j} - P_{\underline{c}j}$	(0.0001)	(0.0001)
Initial average skill rank, 1962	47.88	50.72
$\tilde{x}_{\underline{c}j}$	(0.14)	(0.13)
Change in average skill rank 1962–1975	4.43	− 2.92
$\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}$	(0.22)	(0.21)
Under estimated model:		
Change in avg. skill rank, 1962–1975 at initial skill premia	3.27	3.46
$\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}; \tilde{\mathbf{x}}_{\bar{c},L+1:J}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}}; \tilde{\mathbf{x}}_{\underline{c},L+1:J})$	(0.22)	(0.24)
Share of obs. change explained by change in skill premia	0.2617	2.1860
$1 - \frac{\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}; \tilde{\mathbf{x}}_{\bar{c},L+1:J}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}}; \tilde{\mathbf{x}}_{\underline{c},L+1:J})}{\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}}$	(0.0206)	(0.1636)
Substitution parameter	5.72	
ρ	(1.65)	
[Implied elasticity of substitution $\frac{1}{\rho-1}$]	[0.2120]	

Notes. Data are from the military enlistment sample covering birth cohorts 1962–1975. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. In Panel A, estimates of $\overline{\mathbf{x}}_c$ and $\mathbf{P}_c$ follow Figure I with the linear fit used as our estimate of $\mathbf{P}_c$. Estimates of $\tilde{\mathbf{x}}_c(\cdot)$ follow the proof of Proposition 1. The unknown parameters are ρ and $\left\{\mathbf{K}_c, \overline{S}_c\right\}_{c=\underline{c}}^{\bar{c}}$. Take $\overline{\mathbf{x}}_c$ as our estimate of $\tilde{\mathbf{x}}_c$. Then estimate the elasticity of substitution $\frac{1}{\rho-1}$ following equation (7). Next, estimate the relative cost parameters $\frac{K_{c2}}{K_{c1}}$ in each cohort c following equation (8). From the normalization used in the proof of Proposition 1, estimate K_{c1} following equation (9), from which estimate K_{c2} using the ratio $\frac{K_{c2}}{K_{c1}}$. Finally, estimate the skill budget $\overline{S}_c$ following equation (10). In Panel B, estimates follow Section VI, with $L = 2$ and $J = 3$. We estimate $\mathbf{P}_{c,1:L}$ from earnings regressions that control for a standardized measure of noncognitive skill, excluding from the sample any worker missing information on noncognitive skill. The rest of the analysis follows similarly to Panel A, following the logic in the proof of Proposition 3.

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Figure IV shows the evolution of logical reasoning and vocabulary knowledge skill in the data and in the counterfactual scenario in which the lifetime skill premia $\mathbf{P}_c$ remain constant at their initial level $\mathbf{P}_{\underline{c}}$. In the counterfactual scenario, logical reasoning skill increases by 2.8 percentile points instead of 4.4 as in the actual data. Vocabulary knowledge skill increases by 3.0 percentile points rather than falling by 2.9 percentile points. In this sense, according to the model, changes in the lifetime skill premia $\mathbf{P}_c$ account for 36.8% of the increase in logical reasoning skill (with a standard error of 1.7%), and for more than the entire decline in vocabulary knowledge skill.

To unpack the findings in Figure IV, begin with estimation of the elasticity of substitution $\frac{1}{\rho-1}$. Under Assumption 1, all long-term change in relative skill levels across cohorts must be due to change in relative skill premia. In particular, the elasticity of substitution $\frac{1}{\rho-1}$ can be estimated as the ratio of the long-term change in relative skill levels to the long-term change in relative skill premia. Figure II, Panel B illustrates by plotting the log of the relative estimated average skill level $\ln(\frac{\bar{x}_{c1}}{\bar{x}_{c2}})$ against the log of the relative estimated (linearized) skill premia $\ln(\frac{P_{c1}}{P_{c2}})$. Under Assumption 1, the linear relative supply curve $\ln(\frac{\tilde{x}_{\underline{c}1}(\cdot)}{\tilde{x}_{\underline{c}2}(\cdot)})$ defined by the estimated skill supply function $\tilde{\mathbf{x}}_{\underline{c}}(\cdot)$ for the 1962 birth cohort must pass through the points on the scatterplot for both the 1962 and 1975 birth cohorts. This implies an elasticity of substitution of $\frac{1}{\rho-1} = 0.383$, which is in turn the slope of the line $\ln(\frac{\tilde{x}_{\underline{c}1}(\cdot)}{\tilde{x}_{\underline{c}2}(\cdot)})$ depicted on the plot.

Next, consider estimation of the remaining parameters of the skill supply function $\tilde{\mathbf{x}}_c(\cdot)$. Given the data, under any elasticity of substitution less than 0.97, the model implies that changes in relative premia alone are too small to explain the large increase in logical reasoning skill. We can therefore infer an upward shift in the first dimension of the skill supply function $\tilde{x}_{c1}(\cdot)$ across cohorts, that is, growth in logical reasoning skill beyond what can be explained by changes in premia alone. And, given Assumption 1, the model implies that there must also have been an upward shift in the second dimension of the skill supply function $\tilde{x}_{c2}(\cdot)$ across cohorts, that is, that vocabulary knowledge would have risen absent changes in skill premia.

Following the constant-elasticity form of the transformation function in equation (4) and the log-linear form of the relative

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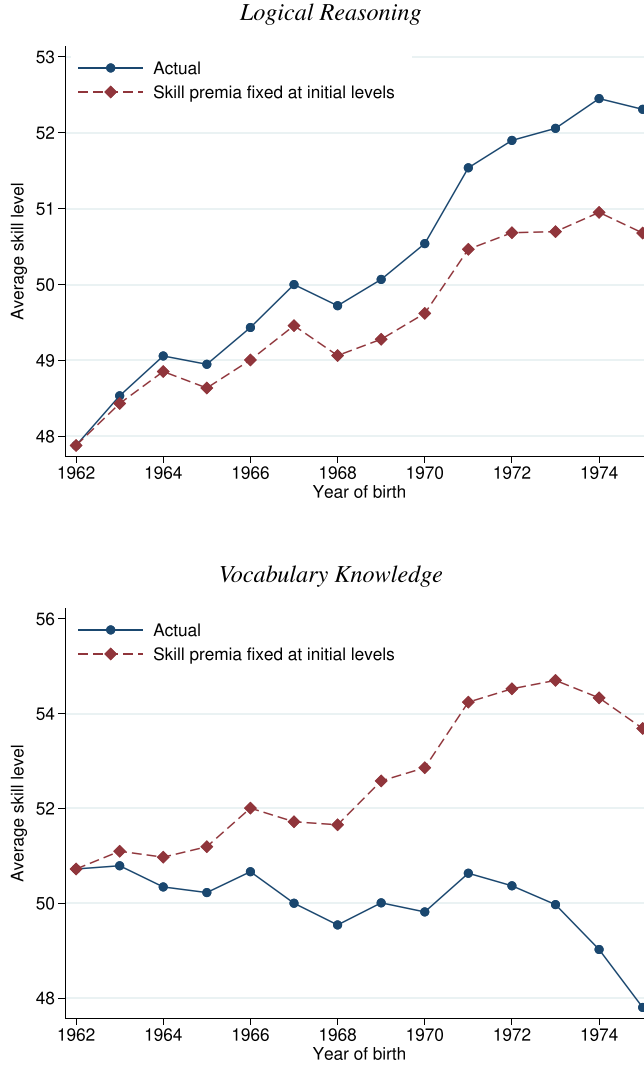


FIGURE IV

Decomposition of Change in Average Skill Level, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. Each plot depicts the average skill $\bar{\mathbf{x}}_c$ for each birth cohort c ("Actual") and the predicted average skill $\bar{\mathbf{x}}_c\left(\mathbf{P}_{\underline{c}}\right)$ under the counterfactual in which lifetime skill premia remain at the level estimated for the 1962 birth cohort ("Skill premia fixed at initial levels"). Skills are expressed as a percentile of the distribution for the 1967 birth cohort.

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supply function in equation (5), our discussion has focused on ratios of skill premia rather than on their differences. It seems likely that a model focusing instead on differences in premia would imply a different conclusion regarding the role of changes in premia in explaining cohort trends in skill levels. To illustrate why, Figure II, Panel C presents an analogue of the scatterplot in Panel B, but replacing log ratios of skill levels and skill premia with their differences. Figure II, Panel C shows that the difference in premia between logical reasoning and vocabulary knowledge did not rise across successive cohorts in the way that Panel B shows that the ratio of premia did. Following Figure I, we find it intuitive that as the premium to vocabulary knowledge fell to a very low level while the premium to logical reasoning skill remained nontrivial, individuals would substitute effort away from vocabulary knowledge, as implied by the constant-elasticity form of the transformation function in equation (4).

Appendix Table I presents sensitivity analysis with respect to choices we have made in constructing the sample and variables for our analysis. Rows (b) and (c) concern the set of birth cohorts we include. Rows (d) and (e) concern the measurement of skills $\mathbf{x}_i$. Row (f) concerns the measurement of earnings w_{it}. Rows (g)–(i) concern the experience levels a and individuals i included in the analysis. Rows (j)–(m) concern the construction of estimates of lifetime skill premia $\mathbf{P}_c$ from estimates of period-specific premia $\mathbf{p}_{c+a,a}$. Rows (n) and (o) concern the smoothing of the estimated lifetime skill premia $\mathbf{P}_c$. Across these different sensitivity analyses, we estimate that changes in lifetime skill premia account for between 29.4% and 46.5% of the increase in logical reasoning skill, which can be compared to our baseline estimate of 36.8%. Online Appendix Figure 14 extends our analysis to a larger set of cohorts, and to women, using the survey sample. We estimate that changes in lifetime skill premia account for a larger share of the increase in logical reasoning skill than in our baseline estimate, though the estimates from the survey sample are less precise than our baseline estimate.

IV.C. Sensitivity to Assumption 1

Figure V shows how our conclusions change as we depart from Assumption 1. The upper plot is for logical reasoning skill and the lower plot is for vocabulary knowledge. Each plot shows the relationship between the estimated share of the change in the given

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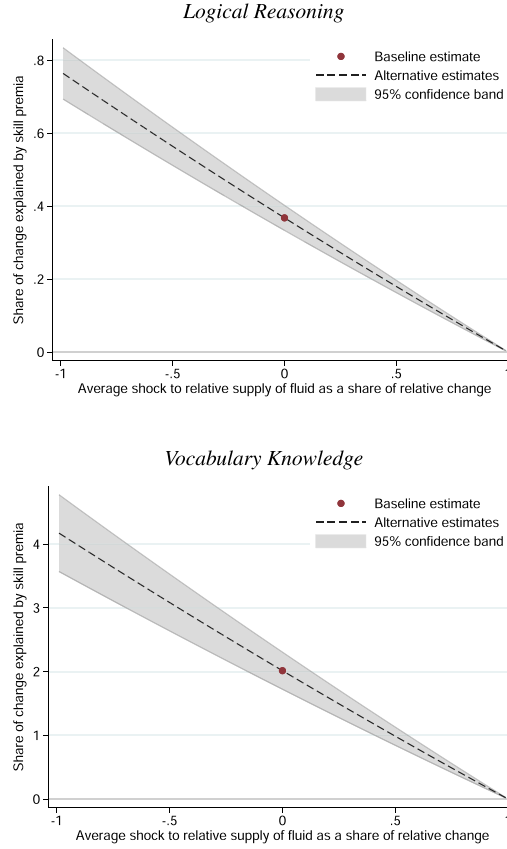


FIGURE V

Sensitivity to Departures from Zero Average Relative Supply Shock

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. In each plot, the curve labeled "Alternative estimates" depicts the estimated share $1 - \frac{\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}}$ of the change in observed skills on dimension j explained by the change in skill premia (y-axis) as a function of the average relative supply shock $-\frac{1}{\bar{c}-\underline{c}} \sum_{c=\underline{c}}^{\bar{c}-1} \left[\ln\left(\frac{K_{c+1,1}}{K_{c+1,2}}\right) - \ln\left(\frac{K_{c1}}{K_{c2}}\right) \right]$ (x-axis). The average relative supply shock is expressed as a share of the estimated change $\ln\left(\frac{\tilde{x}_{\bar{c}1}}{\tilde{x}_{\bar{c}2}}\right) - \ln\left(\frac{\tilde{x}_{\underline{c}1}}{\tilde{x}_{\underline{c}2}}\right)$ in relative skill levels between the 1962 and 1975 birth cohorts, with positive values implying changes in skill-producing technology that favor fluid relative to crystallized intelligence. The shaded region collects pointwise 95% confidence intervals obtained via a nonparametric bootstrap with 50 replicates. The estimate labeled "Baseline estimate" corresponds to the estimate in Table I, Panel A, obtained under Assumption 1.

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skill dimension explained by changes in the lifetime skill premia (y-axis) and the average relative shock to the supply of skill (x-axis). We measure the shock as a fraction of the observed change in relative skill levels. A positive shock implies that changes in skill-producing technology favored fluid intelligence over crystallized intelligence, on average across the cohorts that we study. A negative shock implies the reverse. A shock of zero corresponds to the case in which Assumption 1 holds, and thus to the estimates in Figure IV and Table I, Panel A.

A reader can use Figure V to gauge the effect of a given departure from Assumption 1 on our conclusions. Figure V thus improves transparency in the sense of Andrews, Gentzkow, and Shapiro (2017, 2020) and Andrews and Shapiro (2021).

To illustrate the utility of Figure V with an example, consider the possibility that changes across cohorts in time spent in school shifted the relative supply of different skills. Carlsson et al. (2015) estimate that additional time in school improves performance on the vocabulary knowledge test that we study, and they do not find evidence that additional time in school improves performance on the logical reasoning test. We estimate that relative to the 1962 birth cohort, members of the 1975 birth cohort spent 0.40 more years in school as of the date of test-taking. If at least some of the increase in schooling time would have occurred absent changes in skill premia, then Carlsson et al.'s (2015) analysis implies that increased schooling time can be considered a positive shock to the relative supply of crystallized intelligence, or equivalently a negative shock to the relative supply of fluid intelligence. Figure V shows that if there is a negative shock to the relative supply of fluid intelligence, then our baseline estimates understate the share of the change in skill levels that can be accounted for by changes in skill premia. If we take the entire increase in schooling time as a supply shock and assume no other shocks to the relative supply of the two skill dimensions, we can use the estimates in Carlsson et al. (2015) in tandem with Figure V to calculate that changes in lifetime skill premia explain 53.5% of the observed increase in logical reasoning skill, which is 16.7% points more than our baseline estimate of 36.8% obtained under Assumption 1.[34]

34. Carlsson et al. (2015, table 3, column 1) estimate that an additional 100 days of schooling increases performance in the vocabulary knowledge test by 0.112 standard deviations, relative to the population of test-takers in 1980–1994. Among individuals in our enlistment data, those born in 1975 completed on average 0.40 more years of schooling at enlistment than those born in 1962. As there

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A similar exercise is possible with respect to assumptions about the measurement of skill. To illustrate, Online Appendix Figure 15 depicts our findings regarding trends in actual and counterfactual skills under the assumption that a portion of the cohort trend in logical reasoning skill (upper panel) or vocabulary knowledge skill (lower panel) is spurious. One possible source of spurious trends is a general improvement in test-taking ability (e.g., Neisser 1997; Jensen 1998, 332–33), although this would not by itself explain the simultaneous rise in logical reasoning skill and decline in vocabulary knowledge. Another possible source of spurious trends, specific to vocabulary knowledge, is greater test difficulty for later cohorts due to gradual obsolescence of the words on the test (e.g., Hauser and Huang 1997; Alwin and Pacheco 2012; Roivainen 2014). Online Appendix Figure 15 shows that if a portion of the measured decline in vocabulary knowledge is spurious, our analysis will tend to overstate the role of labor market returns in explaining cohort trends in logical skill, though even if there were no trend in vocabulary knowledge we would still infer that 22.7% (std. err. = 0.6) of the trend in logical skill was due to changes in labor market returns. As more concrete evidence on trends in word usage, Online Appendix Figure 16 shows estimates of the exposure of each cohort to words on example synonym questions for a recent enlistment battery, measuring word exposure based on usage in a major Swedish newspaper. The hypothesis that words on the enlistment battery are more familiar to those born closer to the time of the test design would predict an increasing trend in exposure. We do not find evidence of such a trend.

IV.D. Sensitivity to Controls

We explore the sensitivity of our conclusions to adjusting for covariates. We adjust both the estimated trend in mean skills $\bar{\mathbf{x}}_c$

are roughly 180 schooling days per year in Sweden (Carlsson et al. 2015, 538), this implies an increase of 0.0803 standard deviations in vocabulary knowledge skill. Interpolating around the median test score, we estimate that an increase of 0.0803 standard deviations in vocabulary test score is equivalent to an increase of 3.29 percentile points among those born in 1962. Based on the skill levels reported for the 1962 cohort in Table I Panel A, an increase of 3.29 percentile points in vocabulary knowledge skill would have reduced the log ratio of logical reasoning and vocabulary knowledge skills by 0.063, or by 0.426 of the observed change. Given a relative supply shock of −0.426, Figure V implies that changes in skill premia account for 53.5% of the observed increase in logical reasoning.

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and the estimated trend in lifetime skill premia $\mathbf{P}_c$ with respect to individual-specific, time-invariant covariates $\mathbf{d}_i$ that are normalized to have mean zero among those born in 1967. We adjust the estimated trend in mean skills by estimating a regression of skills x_{ij} on cohort indicators and covariates $\mathbf{d}_i$, excluding the constant.[35] We then treat the coefficients on the cohort indicators as a covariate-adjusted measure of mean skills. We adjust the estimated trend in lifetime skill premia $\mathbf{P}_c$ by including the covariates $\mathbf{d}_i$ in the time-and-age-specific earnings regressions from which we estimate $\mathbf{p}_{t,a}$.

Selection of covariates for inclusion in this exercise is delicate. For adjusting the trend in mean skills, we wish to consider adjusting only for covariates whose cohort trends do not respond to skill premia $\mathbf{P}_c$. For example, if a trend in mean heights would have occurred even absent changes in $\mathbf{P}_c$, then it may be appropriate to adjust the trend in mean skills for the trend in mean heights, and thus to study the effect of skill premia $\mathbf{P}_c$ on the part of the trend in skills that cannot be accounted for by the trend in height. By contrast, if trends in the content of schooling occur in response to changes in skill premia $\mathbf{P}_c$, then these trends are part of the skill investment process that we model, and we do not want to study the effect of skill premia $\mathbf{P}_c$ on only the part of the trend in skills that cannot be accounted for by the trend in the content of schooling.[36] Likewise, for adjusting the trend in lifetime skill premia $\mathbf{P}_c$, we wish to consider adjusting only for covariates that exert a direct effect on earnings independently of their relationship to skills.

Appendix Table II shows how our findings change when we adjust for age at enlistment, an indicator for having completed secondary school at the time of enlistment or at age 18, log(height)

35. In the model in Section II, we may think of this exercise as renormalizing the skill endowment μ_i to have cohort-specific mean $\Gamma\bar{\mathbf{d}}_c$ where $\bar{\mathbf{d}}_c$ is the cohort-specific mean of $\mathbf{d}_i$ and Γ is a matrix whose jth row contains the coefficients on $\mathbf{d}_i$ in the regression of skills x_{ij} on cohort indicators and covariates $\mathbf{d}_i$.

36. Trends in parents' skills may likewise be attributable to (earlier) trends in labor market returns. Suppose, for example, that for each cohort c and skill j, $K_{cj} = \underline{K}_{cj}\bar{x}_{c-g,j}^{-\phi}$ where $\underline{K}_{cj} > 0$ is a scalar, $\bar{x}_{c-g,j}$ is the mean skill level in the parental cohort born $g > 0$ years before cohort c, and $\phi \geqslant 0$ is a parameter governing the intergenerational transmission of skills. Then if we envision a counterfactual change to the time path of skill premia, the skill investment of cohort c will change both due to a direct effect on its incentives, and an indirect effect via the incentives of the parental cohort $c - g$.

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and log(weight) measured at the time of enlistment, and an indicator for being born outside of Sweden. Across these exercises, we find that changes in labor market returns consistently account for at least 35.5% of the increase in logical skill, and for more than the entire decline in vocabulary knowledge skill.

IV.E. Heterogeneity

Appendix Table III shows how our findings change when we estimate the model separately for workers with below- versus above-median parental earnings.[37] We estimate that changes in skill premia explain 1.3 percentage points more of the increase in logical reasoning skill for those whose parents have above-median earnings than for those whose parents have below-median earnings, though the difference is not statistically significant (std. err. = 4.3).

V. Trends in Emphasis among Parents, Schools, and Occupations

Sections V.A and V.B explore whether parents and schools increasingly emphasize reasoning over knowledge. Section V.C explores whether changes in the occupation mix favor reasoning-intensive as opposed to knowledge-intensive occupations. Evidence that parents, schools, and occupations have shifted to emphasize reasoning over knowledge does not, on its own, establish that changes in production technology are driving changes in skill investment. Such evidence can, however, serve to make tangible some of the real-world processes that underlie the skill investment decision modeled in Section II.B and the production economy modeled in Section II.A.

V.A. Parents

Figure VI, Panel A depicts trends in the perceived importance of different skills among parents, as reported in the survey described in Section III.B. Parents of more recent birth cohorts put more emphasis on reasoning skills and less emphasis on knowledge, compared to parents of earlier birth cohorts. Panel B depicts trends in respondents' perception of the importance of different

37. To nest this exercise in the model in Section II, we can suppose there are two distinct labor markets, one for each group of workers, with the two markets potentially linked by a common production function $F_t(\cdot)$.

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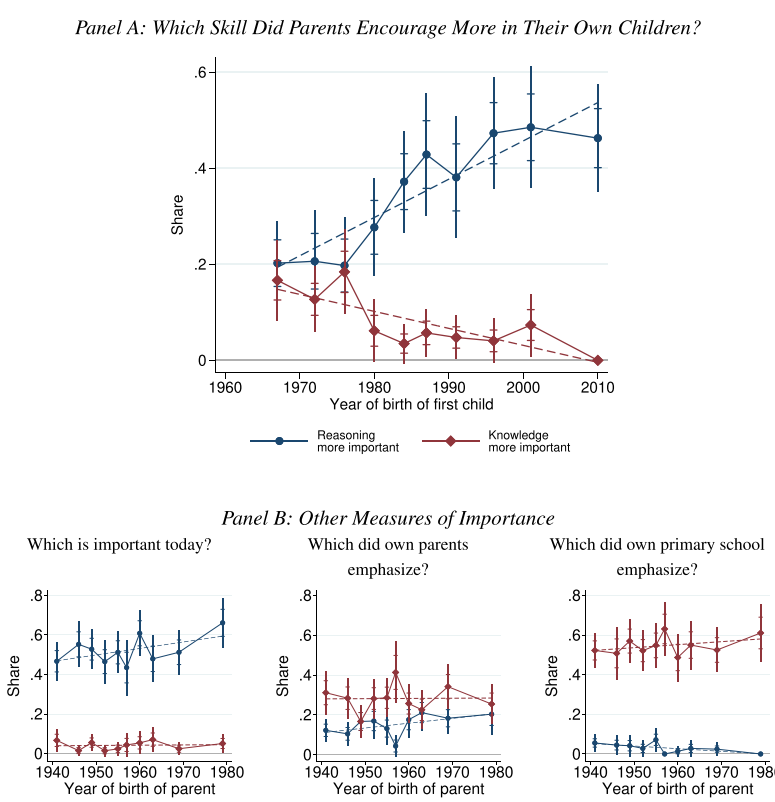


FIGURE VI

Trends in the Perceived Importance of Different Skills in the Survey of Parents' Perceptions

Data are from the original survey of parents' perceptions described in Section III.B. Each figure shows the fraction of respondents rating reasoning as more important (circles) and the fraction rating knowledge as more important (diamonds), separately by decile of the birth cohort of the respondent's first child (Panel A) or of the respondent (Panel B), with deciles labeled by the integer-rounded mean year of birth within the decile. Each plot depicts 95% pointwise confidence intervals (inner intervals, marked by dashes) and 95% uniform confidence bands (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates, stratified by birth cohort decile. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

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skills in today's society, how much their own parents emphasized each skill, and how much their own primary school emphasized each skill. There is some visual evidence that younger parents perceive logical skills to be more important than do older parents. Parents' perceptions of what skills were emphasized by their own parents and primary schools do not show a clear trend.

V.B. Schools

We can also investigate changes in school curricula over the period we study. We focus on primary schooling because Figure III suggests that the trends in skill levels that we study emerge at young ages. The primary school curriculum in Sweden is summarized in an official Curriculum (Läroplan) that is revised from time to time. Meeting society's demands is an explicit goal of the primary schooling system,[38] and although vocational training is not given in primary school, the needs of the workplace have sometimes played a direct role in the development of the Curriculum.[39]

Scholars of pedagogy in Sweden have noted a trend in the Curricula toward greater emphasis over time on problem solving and critical thinking. For example, in an investigation of long-term trends in the teaching of scientific inquiry, Johansson and Wickman (2012) conclude that "The early Curricula of 1962 and 1969 lack the goal that students should learn to ask questions, formulate hypotheses or participate in the planning of investigations. That students should learn to formulate questions is first described in the 1980 Curriculum" (205). Similar trends have been observed in other areas of study.[40] These trends seem consistent with a greater emphasis on reasoning as compared with

38. For example, the first paragraph of the first section of the 1962 Curriculum states a goal of helping students develop into "capable and responsible members of society" (Skolöverstyrelsen 1962, 13). The 1980 Curriculum repeats this language, quoting it as part of the Education Act (Skolöverstyrelsen 1980, 13).

39. For example, the 1962 Curriculum partly reflected the findings from systematic interviews of supervisors and employees regarding the knowledge demands of the workplace (Statens offentliga utredningar 1960, 500–508; Dahl 1999, 43).

40. Löfdahl (1987) studies the physics Curriculum but also describes a more general evolution from 1962 to 1980 toward more emphasis on creativity and critical thinking (see also Johansson and Wickman 2012, 199). Prytz (2015, 317) studies the mathematics Curriculum and notes a trend since the 1960s toward less emphasis on performing calculations. Dahlbäck and Lyngfelt (2017, 167–68) study the evolution of the Curriculum and note that, compared to the 1969 Curriculum, the 1980 Curriculum places greater emphasis on the creative use of language.

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knowledge,[41] though we note that in our survey, parents' perceptions of their own primary schooling experience do not reflect such a trend (see Figure VI, Panel B).

Figure VII presents an original quantitative analysis of trends in emphasis in the Curricula. Based on a close reading of the Curricula, we selected a set of keywords related to reasoning and knowledge. For each cohort, we calculate the relative frequency of keywords related to reasoning versus knowledge during the cohort's primary school years. The figure shows a trend across cohorts toward greater emphasis on reasoning relative to knowledge. Online Appendix Figure 17 lists the set of keywords we study and provides more details on data construction.

V.C. Occupations

Figure VIII shows trends across cohorts in the average reasoning versus knowledge intensity of occupations. We construct the series as follows. First, we measure the relative reasoning versus knowledge intensity of occupations in Sweden by matching occupations to those in the United States and taking data on the importance of different abilities and knowledge from the O*NET 25.0 database (U.S. Department of Labor, Employment and Training Administration 2020). Second, we compute for each occupation the percentile rank in the distribution of reasoning versus knowledge intensity of occupations for the 1967 cohort. Finally, we take the weighted average across occupations in each cohort using as weights either total employment or total earnings among the men in the enlistment sample.

Figure VIII shows evidence of a trend toward relatively more reasoning-intensive occupations. The average man born in 1975 is employed in an occupation that is 2.2 percentile points more reasoning-intensive (relative to knowledge-intensive) than the average man born in 1962. The average krona earned by a man born in 1975 is earned by a man in an occupation 3.3 percentile points more reasoning-intensive than the average krona earned by a man born in 1962. Online Appendix Figure 18 shows trends in

41. Larsson (2011) situates these trends in a transition from realism to progressivism in education. Trends toward greater emphasis on critical thinking and less emphasis on rote knowledge have been noted in many contexts, not just Sweden (see, e.g., Darling-Hammond et al. 2020). Bietenbeck (2014) finds using test score data from the United States that modern teaching practices promote reasoning skills, whereas traditional teaching practices promote factual knowledge.

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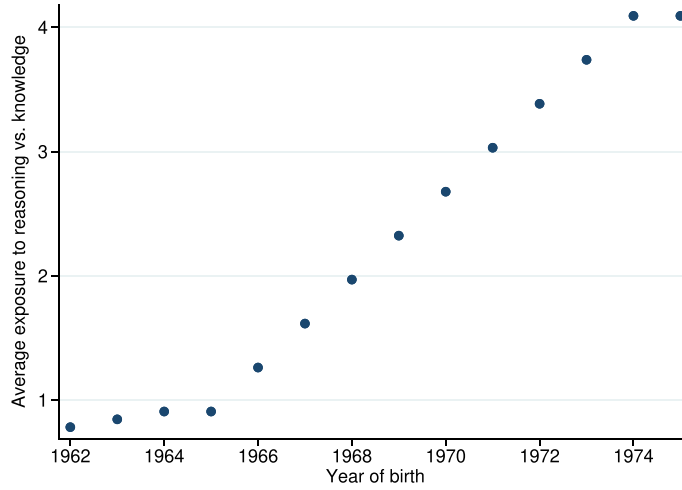


FIGURE VII

Trends in Emphasis on Reasoning versus Knowledge in Swedish Primary School Curricula

The plot shows the trend across birth cohorts in the emphasis on reasoning relative to knowledge in the Swedish primary school Curricula (Läroplan för grundskolan) prevailing during each cohort's primary schooling. We construct the series as follows. First, we associate each school year from 1963 through 1991 with the prevailing Curriculum, treating the 1962 Curriculum (Skolöverstyrelsen 1962) as prevailing from 1963 through 1971, the 1969 Curriculum (Skolöverstyrelsen 1969) as prevailing from 1972 through 1981, and the 1980 Curriculum (Skolöverstyrelsen 1980) as prevailing from 1982 through 1991. Second, for each Curriculum we obtain the ratio of the number of appearances of keywords related to reasoning to the number of appearances of keywords related to knowledge. We choose these keywords based on a close reading of the Curricula; see Online Appendix Figure 17 for details. Third, for each cohort, we define the average exposure to reasoning versus knowledge as the average of the ratio of keyword appearances over the cohort's primary school years, which we take to be the school years beginning in the fall of the year that members of the cohort turn 7 and ending in the spring of the year that members of the cohort turn 16.

shares of total employment and total earnings separately for each occupation.

It is important to make the caveat that the concepts of reasoning and knowledge we measure here do not correspond exactly to those measured by the enlistment tests we study, that the join between Swedish and U.S. occupation codes is imperfect, and that the O*NET scores are static, so the scores do not reflect changes over time in the demands of different occupations. Still, we find the pattern in Figure VIII interesting in light of the growth in

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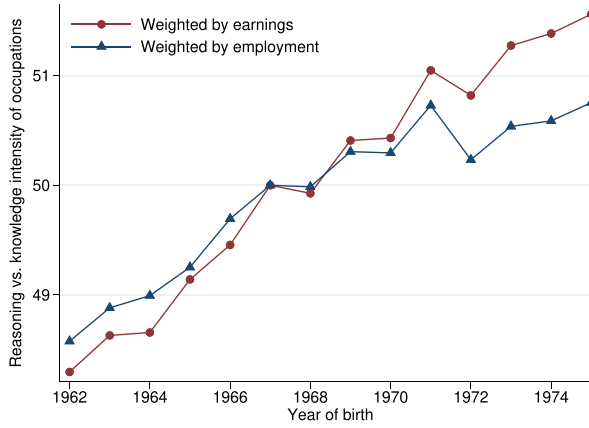


FIGURE VIII

Trends in the Reasoning versus Knowledge Intensity of Men's Occupations in Sweden

The plot shows the trend across birth cohorts in the reasoning versus knowledge intensity of occupations in the Swedish Occupational Register, measured as the mean percentile rank of the reasoning versus knowledge intensity of the given cohort's occupations in the distribution of either total employment ("Weighted by employment") or total earnings ("Weighted by earnings") for the cohort 1967. We measure the distribution of employment and earnings across occupations in the Swedish Occupational Register using data on employment histories from 2004 onward from Statistics Sweden (2021), using four-digit Swedish Standard Classification of Occupations 96 codes, and taking each individual's occupation to be the one observed in the available year closest to the year the individual turns 40. For each O*NET 25.0 (2020) occupation we define the total importance of reasoning abilities by summing the importance scores of Inductive, Deductive, and Mathematical Reasoning abilities and dividing by the highest possible sum. Similarly, we define the total importance of knowledge by summing the importance scores of all knowledge categories and dividing by the highest possible sum. We then define the reasoning versus knowledge intensity of each O*NET 25.0 (2020) occupation by taking the log of the ratio of the total importance of reasoning abilities to the total importance of knowledge. We define the reasoning versus knowledge intensity of each Standard Occupational Classification 2010 (SOC 2010) occupation by taking the unweighted average reasoning versus knowledge intensity of all corresponding occupations in O*NET 25.0 (2020). We match the occupations in the Swedish Occupational Register to SOC 2010 occupations by using the crosswalks from Statistics Sweden (2016c) and U.S. Bureau of Labor Statistics (2015), manually excluding some matches to improve accuracy. We define the reasoning versus knowledge intensity of each occupation in the Swedish Occupational Register by taking the employment-weighted mean reasoning versus knowledge intensity of all corresponding SOC 2010 occupations, using May 2018 OES employment estimates (U.S. Bureau of Labor Statistics 2019) as weights. Each series is normalized by adding a constant so that its value for the 1967 cohort is 50. This figure includes information from the O*NET 25.0 Database by the U.S. Department of Labor, Employment and Training Administration (USDOL/ETA). Used under the CC BY 4.0 license. O*NET® is a trademark of USDOL/ETA. We have modified all or some of this information. USDOL/ETA has not approved, endorsed, or tested these modifications.

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the relative premium to fluid intelligence that we document in Section IV.

VI. Noncognitive Skills

There is evidence of rising labor-market returns to noncognitive skill (e.g., Deming 2017; Edin et al. 2022). We can extend our analysis to incorporate noncognitive skills. Suppose that dimensions $j \in \{1, \ldots, L\}$, for $2 \leqslant L < J$ are dimensions of cognitive skill, and the remaining dimensions $j \in \{L+1, \ldots, J\}$ are dimensions of noncognitive skill. Suppose further that

$$S_c(\tilde{\mathbf{x}}) = s_c\left(\left(\sum_{j=1}^{L} K_{cj}^{\rho-1}\tilde{x}_j^{\rho}\right)^{\frac{1}{\rho}}, \tilde{\mathbf{x}}_{L+1:J}\right), \tag{6}$$

where $\tilde{\mathbf{x}}_{L+1:J} = (\tilde{x}_{L+1}, \ldots, \tilde{x}_J)$ is the noncognitive skill investment and $s_c(\cdot)$ is an aggregator strictly increasing in its first argument.[42] We suppose conditions on $s_c(\cdot)$ sufficient to ensure a unique, strictly positive solution $\tilde{\mathbf{x}}_c(\mathbf{P}_c)$ to the worker's skill investment problem for any $\mathbf{P}_c > 0$. We define a cognitive skill supply function $\tilde{\mathbf{x}}_{c,1:L}(\cdot; \mathbf{x}_{L+1:J})$ that describes the optimal level of cognitive skill investment $\tilde{\mathbf{x}}_{c,1:L} = (\tilde{x}_{c,1}, \ldots, \tilde{x}_{c,L})$ for workers in cohort c given any lifetime skill premia $\mathbf{P}_c > 0$ and any level $\mathbf{x}_{L+1:J}$ of noncognitive skill investment.

For each worker i we observe

$$\hat{\mathbf{x}}_i = (\mathbf{x}_{i,1:L}, \mathbf{A}_{c(i)}(\mathbf{x}_{i,L+1:J})),$$

where $\mathbf{A}_c(\cdot)$ is a cohort-specific, possibly unknown affine map. The presence of the map $\mathbf{A}_c(\cdot)$ reflects the fact that, in our data, the measure of noncognitive skill is standardized and thus not directly comparable across cohorts.[43]

42. An example is the two-level constant elasticity function (e.g., Sato 1967; Goldin and Katz 2008, Chapter 8, equations 1 and 2):

$$s_c\left(\left(\sum_{j=1}^{L} K_{cj}^{\rho-1}\tilde{x}_j^{\rho}\right)^{\frac{1}{\rho}}, \tilde{\mathbf{x}}_{L+1:J}\right) = \left(\lambda\left(\sum_{j=1}^{L} K_{cj}^{\rho-1}\tilde{x}_j^{\rho}\right)^{\frac{\sigma}{\rho}} + (1-\lambda)\left(\sum_{j=L+1}^{J} K_{cj}^{\nu-1}\tilde{x}_j^{\nu}\right)^{\frac{\sigma}{\nu}}\right)^{\frac{1}{\sigma}},$$

where ν, σ, and λ are parameters.

43. Edin et al. (2022, Appendix A1.2) discuss the implications of standardization for the estimation of returns to noncognitive skill.

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Analogous to our baseline analysis, from data on each cohort's cognitive skill premia $\mathbf{P}_{c,1:L}$ and mean observed skill levels $\hat{\mathbf{x}}_c$, it is possible to identify the cognitive skill supply function $\tilde{\mathbf{x}}_{c,1:L}(\cdot;\tilde{\mathbf{x}}_{c,L+1:J})$ where noncognitive skill $\tilde{\mathbf{x}}_{c,L+1:J} = \tilde{\mathbf{x}}_{c,L+1:J}(\mathbf{P}_c)$ is fixed at its equilibrium value for each cohort.

PROPOSITION 3. Under Assumption 1, if $\frac{P_{\bar{c}1}}{P_{\bar{c}2}} \neq \frac{P_{\underline{c}1}}{P_{\underline{c}2}}$, then the cognitive skill supply function $\tilde{\mathbf{x}}_{c,1:L}(\cdot;\tilde{\mathbf{x}}_{c,L+1:J})$ for each cohort c is identified from data $\left\{\left(\alpha\mathbf{P}_{c,1:L}, \hat{\mathbf{x}}_c\right)\right\}_{c=\underline{c}}^{\bar{c}}$, where the scalar $\alpha > 0$ may be unknown.

Our assumptions are also sufficient to identify the lifetime cognitive skill premia up to scale.

PROPOSITION 4. Under Assumption 2, for some scalar $\alpha > 0$, a multiple $\alpha\mathbf{P}_{c,1:L}$ of the lifetime cognitive skill premia for each cohort c is identified from the conditional expectation function of the log of earnings,

$$\mathrm{E}(\ln(w_{it})|\hat{\mathbf{x}}_i = \hat{\mathbf{x}},\ \mathbf{d}_{it} = \mathbf{d},\ c(i) = c),$$

for each time period $t \in \{c+1, \ldots, c+A\}$.

Notice that our assumptions are not generally sufficient to identify the lifetime noncognitive skill premia $\mathbf{P}_{c,L+1:J}$ up to scale due to the presence of the map $\mathbf{A}_c(\cdot)$.

Following the logic of Propositions 3 and 4 and their proofs, we estimate the cognitive skill supply function as follows. First, we reestimate lifetime skill premia $\mathbf{P}_c$ following the procedure outlined in Section IV.A, but including the standardized measure of noncognitive skill as an additional covariate in each earnings regression. Second, we estimate the cognitive skill supply function $\tilde{\mathbf{x}}_{c,1:L}(\cdot;\tilde{\mathbf{x}}_{c,L+1:J})$ following the steps we used to estimate the skill supply function in Section IV.B, but using the reestimated lifetime skill premia.

Table I, Panel B presents our estimates. The estimated cognitive skill supply function implies that fixing the level of noncognitive skill at its equilibrium level, changes in labor market returns account for 26.2% of the increase in logical skill (with a standard error of 2.1%), and for more than the entire decline in vocabulary knowledge skill. The estimated role of changing labor market returns reported in Panel B is meaningfully smaller than in our

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baseline analysis reported in Panel A, as is the estimated elasticity of substitution.

VII. Conclusions

We develop a quantitative economic model of the evolution of multidimensional skills across cohorts. We estimate the model using administrative data from Sweden. The estimated model implies that a significant portion of the puzzling "Flynn effect" of rising fluid intelligence is due to substitution in investment across different dimensions of skill. The model also explains the decline in crystallized intelligence across cohorts in our setting. The model is consistent with evidence of a trend toward greater emphasis on reasoning relative to knowledge among parents, schools, and occupations. We extend our analysis to incorporate noncognitive skill. We conclude that it is fruitful to incorporate market-driven incentives into the analysis of cohort trends in measured intelligence.

We treat the labor demand side of our model abstractly and do not offer a detailed account of the causes of cohort trends in measured labor market returns to skill. Our analysis does, however, suggest some possible explanations for trends in labor market returns to skill. We estimate an increase in the overall supply of skill across cohorts. All else equal, an increase in the supply of skill would tend to lower its return, consistent with our finding of declining returns to cognitive skill across cohorts. Likewise, our finding of an increase in the relative return to reasoning, as compared with knowledge, seems consistent with the trends in occupational composition that we document. We think that developing a more detailed model of skill demand that can be combined with our model of skill supply to explain cohort trends in returns to skill is an interesting direction for future work.

Appendix A: Proofs

Proof of Proposition 1. From Assumption 1 and equation (5) we have that

$$\frac{1}{\rho - 1} = \frac{\ln\left(\frac{\tilde{x}_{\bar{c}1}}{\tilde{x}_{\bar{c}2}}\right) - \ln\left(\frac{\tilde{x}_{\underline{c}1}}{\tilde{x}_{\underline{c}2}}\right)}{\ln\left(\frac{P_{\bar{c}1}}{P_{\bar{c}2}}\right) - \ln\left(\frac{P_{\underline{c}1}}{P_{\underline{c}2}}\right)}, \tag{7}$$

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where the existence of the ratio on the right is guaranteed because $\frac{P_{\tilde{c}1}}{P_{\tilde{c}2}} \neq \frac{P_{c1}}{P_{c2}}$. Thus ρ is identified.

Because $\mathbf{P}_c > 0$, an analogue of equation (5) holds for any pair of dimensions $(1, j)$. Thus given ρ the ratio $\frac{K_{cj}}{K_{c1}}$ is identified for all c and j via the relation

$$\ln\left(\frac{K_{cj}}{K_{c1}}\right) = \ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{cj}}\right) - \frac{1}{\rho - 1}\ln\left(\frac{P_{c1}}{P_{cj}}\right). \tag{8}$$

From the budget constraint in expression (2) and the transformation function in equation (4), observe that multiplying $\mathbf{K}_c$ by any positive constant κ is equivalent to multiplying $\overline{S}_c$ by $\kappa^{\frac{1-\rho}{\rho}}$. Therefore fix the scale of $\mathbf{K}_c$ by supposing that its average element equals 1, that is, $\sum_{j=1}^{J} K_{cj} = J$. Then $\sum_{j=1}^{J} K_{cj} = \sum_{j=1}^{J}\left(\frac{K_{cj}}{K_{c1}}\right) K_{c1} = K_{c1}\sum_{j=1}^{J}\left(\frac{K_{cj}}{K_{c1}}\right) = J$, which from equation (8) implies

$$K_{c1} = \frac{J}{\sum_{j=1}^{J} \frac{\tilde{x}_{c1}}{\tilde{x}_{cj}}\left(\frac{P_{cj}}{P_{c1}}\right)^{\frac{1}{\rho-1}}}. \tag{9}$$

Thus $\mathbf{K}_c$ is identified for each cohort c given ρ and the ratios $\frac{K_{cj}}{K_{c1}}$.

Finally, $\overline{S}_c$ is identified for all c given ρ and $\mathbf{K}_c$ because, from the solution to the worker's problem,

$$\overline{S}_c = \frac{\tilde{x}_{c1}\left(\sum_{j=1}^{J} P_{cj}^{\frac{\rho}{\rho-1}} K_{cj}^{-1}\right)^{\frac{1}{\rho}}}{P_{c1}^{\frac{1}{\rho-1}} K_{c1}^{-1}}. \tag{10}$$

Proof of Corollary 1. Let $\hat{\mathbf{P}}_c = |\alpha \mathbf{P}_c| = |\alpha| \mathbf{P}_c$ for $\alpha \neq 0$. Because $\frac{\hat{P}_{c1}}{\hat{P}_{cj}} = \frac{P_{c1}}{P_{cj}}$ for all c and j, the arguments in the proof of Proposition 1 directly establish identification of ρ and identification of $\mathbf{K}_c$ up to a normalization. Then $\overline{S}_c$ is identified for all c given ρ and $\mathbf{K}_c$ because

$$\overline{S}_c = \frac{\tilde{x}_{c1}\left(\sum_{j=1}^{J} P_{cj}^{\frac{\rho}{\rho-1}} K_{cj}^{-1}\right)^{\frac{1}{\rho}}}{P_{c1}^{\frac{1}{\rho-1}} K_{c1}^{-1}} = \frac{\tilde{x}_{c1}\left(\sum_{j=1}^{J} \hat{P}_{cj}^{\frac{\rho}{\rho-1}} K_{cj}^{-1}\right)^{\frac{1}{\rho}}}{\hat{P}_{c1}^{\frac{1}{\rho-1}} K_{c1}^{-1}}.$$

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Proof of Proposition 2. From equation (1) we have that for each period t

$$\begin{aligned}
&\mathrm{E}(\ln(w_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) \\
&\quad = \mathrm{E}(B_{t,a(i,t)} + \mathbf{p}'_{t,a(i,t)}\mathbf{x}_i + \ln(z_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) \\
&\quad = B_{t,t-c} + \mathbf{p}'_{t,t-c}\mathbf{x} + \mathrm{E}(\ln(z_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c).
\end{aligned}$$

Because $\mathbf{x}_i = \tilde{\mathbf{x}}_{c(i)} + \mu_i$ for all i, we also have that

$$\begin{aligned}
&\mathrm{E}(\ln(z_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) \\
&\quad = \mathrm{E}(\ln(z_{it})|\tilde{\mathbf{x}}_c + \mu_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) \\
&\quad = \mathrm{E}(\ln(z_{it})|\mu_i = \mathbf{x} - \tilde{\mathbf{x}}_c, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) \\
&\quad = \zeta_{t,t-c} + \tilde{\alpha}\mathbf{p}'_{t,t-c}(\mathbf{x} - \tilde{\mathbf{x}}_c) + \mathbf{d}'\beta_{t,t-c},
\end{aligned}$$

where the last equality uses Assumption 2. It follows that

$$\mathrm{E}(\ln(w_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c) = \tilde{B}_{t,t-c} + \alpha\mathbf{p}'_{t,t-c}\mathbf{x} + \mathbf{d}'\beta_{t,t-c},$$

where $\tilde{B}_{t,t-c} = (B_{t,t-c} + \zeta_{t,t-c} - \tilde{\alpha}\mathbf{p}'_{t,t-c}\tilde{\mathbf{x}}_c)$ and $\alpha = 1 + \tilde{\alpha}$. Since $\tilde{\alpha} \neq -1$, we have $\alpha \neq 0$. Identification of $\mathbf{p}_{t,t-c}$ up to scale is then immediate, from which identification of $\mathbf{P}_c$ up to scale follows directly from equation (3).

Proof of Proposition 3. Recall that the worker maximizes $\mathbf{P}'_{c(i)}\tilde{\mathbf{x}}_i$ subject to $\tilde{\mathbf{x}}_i \geqslant 0$ and $S_{c(i)}(\tilde{\mathbf{x}}_i) \leqslant \overline{S}_{c(i)}$, where $\tilde{\mathbf{x}}_i = \mathbf{x}_i - \mu_i$. Fixing noncognitive skill investment at $\tilde{\mathbf{x}}_{i,L+1:J} = \tilde{\mathbf{x}}_{c(i),L+1:J} \geqslant 0$, and taking account of the form of the transformation function in equation (6), we can rewrite the worker's problem as maximizing $\mathbf{P}'_{c(i),1:L}\tilde{\mathbf{x}}_{i,1:L}$ subject to $\tilde{\mathbf{x}}_{i,1:L} \geqslant 0$ and $(\sum_{j=1}^{L} K_{c(i)j}^{\rho-1}\tilde{x}_j^{\rho})^{\frac{1}{\rho}} \leqslant s_{c(i)}^{-1}(\overline{S}_{c(i)}, \tilde{\mathbf{x}}_{c(i),L+1:J})$, where $s_{c(i)}^{-1}(\overline{S}_{c(i)}, \tilde{\mathbf{x}}_{c(i),L+1:J})$ solves $s_{c(i)}(s_{c(i)}^{-1}(\overline{S}_{c(i)}, \tilde{\mathbf{x}}_{c(i),L+1:J}), \tilde{\mathbf{x}}_{c(i),L+1:J}) = \overline{S}_{c(i)}$, is unique by the strict monotonicity of $s_c(\cdot)$ in its first argument, and is strictly positive because the worker's problem is assumed to have a strictly positive solution. We have demonstrated that the worker's problem of choosing cognitive skills given noncognitive skills is equivalent to the worker's problem in Section II.C, replacing J with L and $\overline{S}_{c(i)}$ with $s_{c(i)}^{-1}(\overline{S}_{c(i)}, \tilde{\mathbf{x}}_{c(i),L+1:J})$. The results of Proposition 1 and Corollary 1 thus apply given Assumption 1.

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Proof of Proposition 4. We have that

$$\begin{aligned}
&\mathrm{E}(\ln(w_{it})|\hat{\mathbf{x}}_i = \hat{\mathbf{x}},\ \mathbf{d}_{it} = \mathbf{d},\ c(i) = c) \\
&\quad = \mathrm{E}(\mathrm{E}(\ln(w_{it})|\mathbf{x}_i = \mathbf{x}, \mathbf{d}_{it} = \mathbf{d}, c(i) = c)|\hat{\mathbf{x}}_i = \hat{\mathbf{x}}) \\
&\quad = \mathrm{E}(\tilde{B}_{t,t-c} + \alpha \mathbf{p}'_{t,t-c}\mathbf{x} + \mathbf{d}'\beta_{t,t-c}|\hat{\mathbf{x}}_i = \hat{\mathbf{x}}) \\
&\quad = \tilde{B}_{t,t-c} + \alpha \mathbf{p}'_{t,t-c,1:L}\mathbf{x}_{1:L} + \alpha \mathbf{p}'_{t,t-c,L+1:J}\mathbf{A}_c^{-1}(\hat{\mathbf{x}}_{L+1:J}) + \mathbf{d}'\beta_{t,t-c},
\end{aligned}$$

where the first step follows from the law of total expectation, the second from the proof of Proposition 2, and the third from the invertibility of $\mathbf{A}_c$. Because $\mathbf{A}_c^{-1}(\cdot)$ is linear in $\hat{\mathbf{x}}_{L+1:J}$, identification of $\mathbf{p}'_{t,t-c,1:L}$ up to scale is immediate, from which identification of $\mathbf{P}_{c,1:L}$ up to scale follows directly from equation (3).

Appendix B: Sensitivity and Heterogeneity Analysis

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APPENDIX TABLE I

SENSITIVITY OF MAIN RESULTS TO DIFFERENT SPECIFICATIONS

	Initial lifetime skill premium, 1962 $P_{\underline{c}j}$		Change in lifetime skill premium $P_{\bar{c}j} - P_{\underline{c}j}$		Initial average skill level $\bar{x}_{\bar{c}j}$		Change in average skill skill level $\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \bar{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}}$	
Specification	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge
(a) Baseline	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3681	2.0151
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0175)	(0.1483)
(b) Exclude birth cohort 1962	0.0047	0.0016	−0.0007	−0.0008	48.53	50.79	4.09	−3.24	0.3940	1.8008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.12)	(0.13)	(0.21)	(0.25)	(0.0250)	(0.1294)
(c) Exclude birth cohort 1975	0.0048	0.0016	−0.0008	−0.0006	47.88	50.72	4.95	−1.84	0.3153	2.9520
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.23)	(0.19)	(0.0114)	(0.3006)
(d) Replace percentile rank with percent of maximum score attained	0.0074	0.0025	−0.0009	−0.0009	59.96	61.07	3.30	−1.04	0.2936	3.2777
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.09)	(0.07)	(0.14)	(0.11)	(0.0122)	(0.3969)
(e) Replace logical reasoning skill with logical-spatial composite	0.0050	0.0020	−0.0010	−0.0006	46.42	50.72	5.10	−2.92	0.4545	2.0408
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.13)	(0.13)	(0.21)	(0.21)	(0.0174)	(0.1486)
(f) Include business income in earnings measure	0.0049	0.0016	−0.0009	−0.0007	47.88	50.72	4.43	−2.92	0.3587	2.0302
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0168)	(0.1486)
(g) Age range 35–55	0.0049	0.0019	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.4393	1.9008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0196)	(0.1396)
(h) Age range 30–60	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3780	1.9992
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0177)	(0.1471)
(i) Restrict to modal full-year workers	0.0043	0.0016	−0.0006	−0.0006	49.07	51.61	3.74	−3.52	0.4653	1.5987
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.14)	(0.23)	(0.21)	(0.0258)	(0.0982)
(j) Extrapolate from ages 35+	0.0048	0.0016	−0.0008	−0.0008	47.88	50.72	4.43	−2.92	0.3591	2.0296
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0174)	(0.1497)

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APPENDIX TABLE I

CONTINUED

Specification	Initial lifetime skill premium, 1962 $P_{\underline{c}j}$		Change in lifetime skill premium $P_{\bar{c}j} - P_{\underline{c}j}$		Initial average skill level $\bar{x}_{\underline{c}j}$		Change in average skill skill level $\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \bar{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}}$	
	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge
(k) Extrapolate from oldest available age	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3703	2.0115
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0179)	(0.1486)
(l) NPV with discount factor 0.93	0.0048	0.0015	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3396	2.0609
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0169)	(0.1519)
(m) NPV with discount factor 0.99	0.0048	0.0017	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3931	1.9750
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0182)	(0.1452)
(n) Quadratic smoothing for estimated skill premium series	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3680	2.0154
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0175)	(0.1483)
(o) No smoothing for estimated skill premium series	0.0050	0.0013	−0.0010	−0.0006	47.88	50.72	4.43	−2.92	0.3085	2.1108
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.14)	(0.13)	(0.23)	(0.20)	(0.0308)	(0.1648)

Notes. This table summarizes the sensitivity of our main results to different specifications. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. In each replicate, for each cohort c, we draw men with replacement from the population in that cohort, and recalculate all data-dependent objects. We exclude three and five bootstrap replicates from the calculation of standard errors for rows (e) and (o), respectively, due to values inconsistent with the model. Row (a) reproduces our baseline estimates from Table I, Panel A. Row (b) changes the initial birth cohort $\underline{c}$ to be those born in 1963, and row (c) changes the final birth cohort $\bar{c}$ to be those born in 1974. Both rows (b) and (c) multiply estimated changes by $\frac{13}{12}$ for comparability with the other specifications. Row (d) replaces the logical reasoning and vocabulary knowledge skill measures with the percent of the maximum possible score attained by the individual. Row (e) replaces the logical reasoning skill measure with the first component from a principal component analysis of logical reasoning and spatial reasoning skill measures for the 1967 birth cohort. Spatial reasoning skills are measured using a task in which individuals are asked to identify a three-dimensional object that corresponds to an unfolded piece of metal (Carlstedt and Mårdberg 1993; Carlstedt 2000). Row (f) incorporates business income into our measure of earnings for 1990–2018. Rows (g) and (h) vary the ages of working life that we consider for estimating the lifetime skill premia $\mathbf{P}_c$. Row (i) excludes individuals for whom the greatest mode of annual months worked in sample years is less than 12. We define an individual as being employed in a given month if that month falls between the first and last month of employment for at least one of the jobs he holds during the year. Rows (j) and (k) vary the ages over which we average the estimated premia $\mathbf{p}_{c+a,a}$ to infer premia for ages for which earnings data are unavailable. Rows (l) and (m) vary the discount factor δ that we use in the calculation of $\mathbf{P}_c$ via equation (3). Rows (n) and (o) use, respectively, a quadratic fit (second-order polynomial) and no smoothing at all, instead of a linear fit, for the relationship between estimated lifetime skill premia and cohort.

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APPENDIX TABLE II

SENSITIVITY OF MAIN RESULTS TO ADJUSTING FOR CONTROL VARIABLES

	Initial lifetime skill premium, 1962 $P_{\underline{c}j}$		Change in lifetime skill premium, 1962–1975 $P_{\bar{c}j} - P_{\underline{c}j}$		Initial average skill rank, 1962 $\bar{x}_{\underline{c}j}$		Change in average skill rank, 1962–1975 $\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{\bar{c}j}(\mathbf{P}_{\bar{c}}) - \bar{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}}$	
Specification	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge
(a) Baseline (no controls)	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3681	2.0151
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0175)	(0.1483)
(b) Age at enlistment (indicators)	0.0047	0.0016	−0.0007	−0.0007	48.21	51.03	4.43	−2.84	0.3596	2.0592
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.13)	(0.13)	(0.23)	(0.21)	(0.0179)	(0.1575)
(c) Completed secondary education at enlistment (indicator)	0.0048	0.0016	−0.0008	−0.0007	47.22	50.03	4.48	−2.86	0.3594	2.0612
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.23)	(0.21)	(0.0175)	(0.1577)
(d) Completed secondary education at age 18 (indicator)	0.0048	0.0016	−0.0008	−0.0007	47.10	49.87	4.15	−3.20	0.3860	1.8431
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.20)	(0.0193)	(0.1196)
(e) log(height) and log(weight) at enlistment	0.0047	0.0015	−0.0008	−0.0006	47.94	50.79	4.47	−2.96	0.3554	2.0301
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0178)	(0.1489)
(f) Born outside Sweden (indicator)	0.0048	0.0016	−0.0008	−0.0007	47.90	50.72	4.30	−3.03	0.3756	1.9370
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.13)	(0.13)	(0.23)	(0.21)	(0.0189)	(0.1376)

Notes. This table summarizes the sensitivity of our main results to adjusting for different control variables. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. In each replicate, for each cohort c, we draw men with replacement from the population in that cohort, and recalculate all data-dependent objects. Row (a) reproduces our baseline estimates with no controls from Table I, Panel A. Each subsequent row includes a different control variable or variables. Control variables are included when estimating cohort- and age-specific skill premia and are used to adjust the estimated average skill levels, following Section IV.D. In each row, we omit individuals with missing or invalid values of the relevant control variables. In specification (b), we control for indicators for the number of years between the person's year of enlistment and year of birth. In specification (c), we define a person as having completed secondary education at enlistment if the person's enlistment date occurs on or after June 1 of the year in which they complete secondary education.

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APPENDIX TABLE III

MODEL IMPLICATIONS FOR DIFFERENT SUBSAMPLES

Specification	Initial lifetime skill premium, 1962 $P_{\underline{c}j}$		Change in lifetime skill premium, 1962–1975 $P_{\bar{c}j} - P_{\underline{c}j}$		Initial average skill rank, 1962 $\bar{x}_{\bar{c}j}$		Change in average skill rank, 1962–1975 $\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{\bar{c}j}(\mathbf{P}_{\bar{c}}) - \bar{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}}$	
	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge
(a) Baseline	0.0048	0.0016	−0.0008	−0.0007	47.88	50.72	4.43	−2.92	0.3681	2.0151
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.14)	(0.13)	(0.22)	(0.21)	(0.0175)	(0.1483)
(b) Below-median parental earnings	0.0044	0.0012	−0.0006	−0.0006	43.59	46.73	3.51	−3.39	0.3518	1.7200
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.17)	(0.21)	(0.29)	(0.29)	(0.0375)	(0.1457)
(c) Above-median parental earnings	0.0048	0.0017	−0.0010	−0.0008	52.43	54.96	4.98	−2.81	0.3646	2.1799
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.21)	(0.20)	(0.31)	(0.30)	(0.0232)	(0.2213)

Notes. This table summarizes the model implications for different subsamples. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. In each replicate, for each cohort c, we draw men with replacement from the population in that cohort, and recalculate all data-dependent objects. We exclude one bootstrap replicate from the calculation of standard errors for row (b) due to values inconsistent with the model. Row (a) reproduces our baseline estimates from Table I, Panel A. Rows (b) and (c) estimate the model for individuals with below- or above-median parental earnings, respectively, in their given cohort. For each sample individual, we define parental earnings as the average lifetime earnings of all biological or adoptive parents, with lifetime earnings given by the average earnings over all ages 30 through 55 observed in the data.

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SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at the *Quarterly Journal of Economics* online.

DATA AVAILABILITY

Data and code replicating the tables and figures in this article can be found in Hermo et al. (2022) in the Harvard Dataverse, https://doi.org/10.7910/DVN/KP9RZX.

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ONLINE APPENDIX FOR "LABOR MARKET RETURNS AND THE EVOLUTION OF COGNITIVE SKILLS: THEORY AND EVIDENCE"

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MIIKA PÄÄLLYSAHO
DAVID SEIM
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April 2022

A IDENTIFICATION OF THE SKILL SUPPLY FUNCTION WITH A SOCIAL MULTIPLIER

Suppose that $K_{cj} = \overline{K}_{cj}\overline{x}_{cj}^{-\upsilon}$ where $\upsilon \in [0,1)$ is a parameter governing the strength of social spillovers in skill investment and $\overline{\mathbf{K}}_c \in \mathbb{R}^J_{>0}$ is a vector of cost parameters. Each worker chooses skill investment taking the average skill $\overline{\mathbf{x}}_{c(i)}$ of their cohort $c(i)$ as given.

Online Appendix Assumption 1. *(Zero average relative supply shock.) We assume that*

$$\frac{1}{\overline{c}-\underline{c}}\sum_{c=\underline{c}}^{\overline{c}-1}\left[\ln\left(\frac{\overline{K}_{c+1,1}}{\overline{K}_{c+1,2}}\right)-\ln\left(\frac{\overline{K}_{c1}}{\overline{K}_{c2}}\right)\right]=0.$$

Online Appendix Proposition 1. *Under Online Appendix Assumption 1, if* $\frac{P_{\overline{c}1}}{P_{\overline{c}2}} \neq \frac{P_{\underline{c}1}}{P_{\underline{c}2}}$*, then the skill supply function* $\tilde{\mathbf{x}}_c(\cdot)$ *for each cohort* c *is identified from data* $\{(\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\overline{c}}$.

Proof of Online Appendix Proposition 1

In the model in Section II.C the skill supply function is given by

$$\tilde{x}_{cj}(\mathbf{P}_c) = \frac{P_{cj}^{\frac{1}{\rho-1}}K_{cj}^{-1}}{\left(\sum_{j'=1}^{J}P_{cj'}^{\frac{\rho}{\rho-1}}K_{cj'}^{-1}\right)^{\frac{1}{\rho}}}\overline{S}_c \tag{OA1}$$

for each skill $j \in \{1,...,J\}$. Recalling that $K_{cj} = \overline{K}_{cj}\bar{x}_{cj}^{-\upsilon}$ and imposing the equilibrium condition that $\tilde{\mathbf{x}}_c = \overline{\mathbf{x}}_c$ we have that

$$\tilde{x}_{cj}(\mathbf{P}_c) = \frac{P_{cj}^{\frac{1}{\rho-1}}\overline{K}_{cj}^{-1}\left(\tilde{x}_{cj}(\mathbf{P}_c)\right)^{\upsilon}}{\left(\sum_{j'=1}^{J} P_{cj'}^{\frac{\rho}{\rho-1}}\overline{K}_{cj'}^{-1}\left(\tilde{x}_{cj'}(\mathbf{P}_c)\right)^{\upsilon}\right)^{\frac{1}{\rho}}}\overline{S}_c \tag{OA2}$$

for each skill $j \in \{1,...,J\}$. Define $\tilde{\mathbf{K}}_c$ such that $\tilde{K}_{cj} = \overline{K}_{cj}^{\frac{1}{1-\upsilon}}$ and notice that $\tilde{\mathbf{K}}_c \in \mathbb{R}^J_{>0}$ and that

$$\frac{1}{\overline{c}-\underline{c}}\sum_{c=\underline{c}}^{\overline{c}-1}\left[\ln\left(\frac{\tilde{K}_{c+1,1}}{\tilde{K}_{c+1,2}}\right) - \ln\left(\frac{\tilde{K}_{c1}}{\tilde{K}_{c2}}\right)\right] = 0$$

by Online Appendix Assumption 1. Define $\tilde{\rho}$ such that

$$\frac{1}{\tilde{\rho}-1} = \frac{1}{(\rho-1)(1-\upsilon)}$$

and notice that $\tilde{\rho} > 1$. Define $\tilde{S}_c = \overline{S}_c^{\frac{\rho}{\tilde{\rho}}}$ and notice that $\tilde{S}_c > 0$. Then the unique solutions to the J equations in (OA2) are given by

$$\tilde{x}_{cj}(\mathbf{P}_c) = \frac{P_{cj}^{\frac{1}{\tilde{\rho}-1}}\tilde{K}_{cj}^{-1}}{\left(\sum_{j'=1}^{J} P_{cj'}^{\frac{\tilde{\rho}}{\tilde{\rho}-1}}\tilde{K}_{cj'}^{-1}\right)^{\frac{1}{\tilde{\rho}}}}\tilde{S}_c \tag{OA3}$$

for each skill $j \in \{1,...,J\}$. Because (OA3) is isomorphic to (OA1), replacing $\mathbf{K}_c$ with $\tilde{\mathbf{K}}_c$, ρ with $\tilde{\rho}$, and $\overline{S}_c$ with $\tilde{S}_c$, and because an analogue of Assumption 1 in the main text holds for $\tilde{\mathbf{K}}_c$, Proposition 1 in the main text applies directly.

B IDENTIFICATION OF LIFETIME SKILL PREMIA WITH MISMEASURED SKILLS

Let $\hat{\mathbf{x}}_i$ denote a measurement of $\mathbf{x}_i$. For simplicity we set aside the role of covariates $\mathbf{d}_{it}$.

Online Appendix Assumption 2. *The measurement error in each cohort c obeys*

$$\mathrm{E}\left(\hat{\mathbf{x}}_i - \mathbf{x}_i | \mu_i = \mu, c\left(i\right) = c\right) = 0 \tag{OA4}$$

and

$$\mathrm{Var}\left(\hat{\mathbf{x}}_i - \mathbf{x}_i | c\left(i\right) = c\right) = \hat{\alpha}\,\mathrm{Var}\left(\hat{\mathbf{x}}_i | c\left(i\right) = c\right), \tag{OA5}$$

where the scalar $\hat{\alpha} \in [0,1)$ *may be unknown.*

Online Appendix Assumption 2 implies that the measurement error in $\hat{\mathbf{x}}_i$ has mean zero conditional on true skills and has variance proportional to both measured and true skills.

Online Appendix Assumption 3. *The values of* z_{it} *in each period t obey*

(OA6)

$$\mathrm{E}\left(\ln\left(z_{it}\right) | \hat{\mathbf{x}}_i - \mathbf{x}_i = \xi, \mu_i = \mu, c\left(i\right) = c\right) = \mathrm{E}\left(\ln\left(z_{it}\right) | \mu_i = \mu, c\left(i\right) = c\right) = \zeta_{t,t-c} + \tilde{\alpha}\mathbf{p}_{t,t-c}^{'}\mu,$$

where the scalars $\zeta_{t,t-c}$ *and* $\tilde{\alpha} \geq 0$ *may be unknown.*

Online Appendix Assumption 3 implies that a version of Assumption 2 in the main text holds, and that unobserved determinants of log earnings are mean-independent of the measurement error in skills.

Online Appendix Assumptions 2 and 3 are sufficient to identify the cohort-and-period-specific skill premia $\mathbf{p}_{t,t-c}$, and hence the lifetime skill premia $\mathbf{P}_c$, up to scale, from the conditional expectation function of the log of earnings given measured skills.

Online Appendix Proposition 2. *Under Online Appendix Assumptions 2 and 3, for some scalar* $\alpha > 0$*, a multiple* $\alpha\mathbf{P}_c$ *of the lifetime skill premia for each cohort c is identified from the conditional expectation function of the log of earnings given measured skills,*

$$\mathrm{E}\left(\ln\left(w_{it}\right) | \hat{\mathbf{x}}_i = \hat{\mathbf{x}}, c\left(i\right) = c\right),$$

for each time period $t \in \{c+1, ..., c+A\}$.

Proof of Online Appendix Proposition 2

Fix a cohort c and period t. From (OA4) and (OA5) we have that

$$\mathrm{Var}\left(\hat{\mathbf{x}}_i | c\left(i\right) = c\right) = \left(1 - \hat{\alpha}\right)^{-1} \mathrm{Var}\left(\mathbf{x}_i | c\left(i\right) = c\right).$$

From (1) in the main text, (OA4), and (OA6) we have that

$$\begin{aligned}
\mathrm{Cov}\left(\hat{\mathbf{x}}_i, \ln\left(w_{it}\right) | c\left(i\right) = c\right) &= \mathrm{Cov}\left(\hat{\mathbf{x}}_i, \mathbf{p}_{t,t-c}^{'} \mathbf{x}_i + \ln\left(z_{it}\right) | c\left(i\right) = c\right) \\
&= \mathrm{Cov}\left(\mathbf{x}_i, \left(1 + \tilde{\alpha}\right) \mathbf{p}_{t,t-c}^{'} \mathbf{x}_i | c\left(i\right) = c\right) \\
&= \left(1 + \tilde{\alpha}\right) \mathrm{Var}\left(\mathbf{x}_i | c\left(i\right) = c\right) \mathbf{p}_{t,t-c}.
\end{aligned}$$

The population regression of $\ln\left(w_{it}\right)$ on $\hat{\mathbf{x}}_i$ and a constant therefore yields coefficients

$$\mathrm{Var}\left(\hat{\mathbf{x}}_i | c\left(i\right) = c\right)^{-1} \mathrm{Cov}\left(\hat{\mathbf{x}}_i, \ln\left(w_{it}\right) | c\left(i\right) = c\right) = \alpha \mathbf{p}_{t,t-c}$$

for $\alpha = \left(1 - \hat{\alpha}\right)\left(1 + \tilde{\alpha}\right) > 0$. Because the population regression is available from the conditional expectation function, identification of $\mathbf{p}_{t,t-c}$ up to scale is then immediate, from which identification of $\mathbf{P}_c$ up to scale follows directly from equation (3) in the main text.

C ADDITIONAL TABLES AND FIGURES

ONLINE APPENDIX TABLE 1
NUMBER OF INDIVIDUALS BY BIRTH COHORT, MILITARY ENLISTMENT AND SURVEY SAMPLES

(a) *Military Enlistment Data*

Birth cohort	Number of individuals
1962	52,317
1963	55,526
1964	58,639
1965	55,018
1966	39,056
1967	47,767
1968	49,965
1969	48,850
1970	48,815
1971	51,108
1972	50,824
1973	47,353
1974	47,923
1975	38,069
Total	691,230

(b) *Survey Data*

Birth cohort	Number of individuals
1948	5,361
1953	4,699
1967	3,907
1972	3,899
1977	1,966
Total	19,832

Notes. Each panel shows the number of individuals in each birth cohort for whom we measure valid logical reasoning and vocabulary knowledge test scores. Panel (a) shows counts for the military enlistment data. Panel (b) shows counts for the survey data.

ONLINE APPENDIX TABLE 2
TRENDS IN LIFETIME SKILL PREMIA USING SURVEY TEST SCORES AS INSTRUMENTS

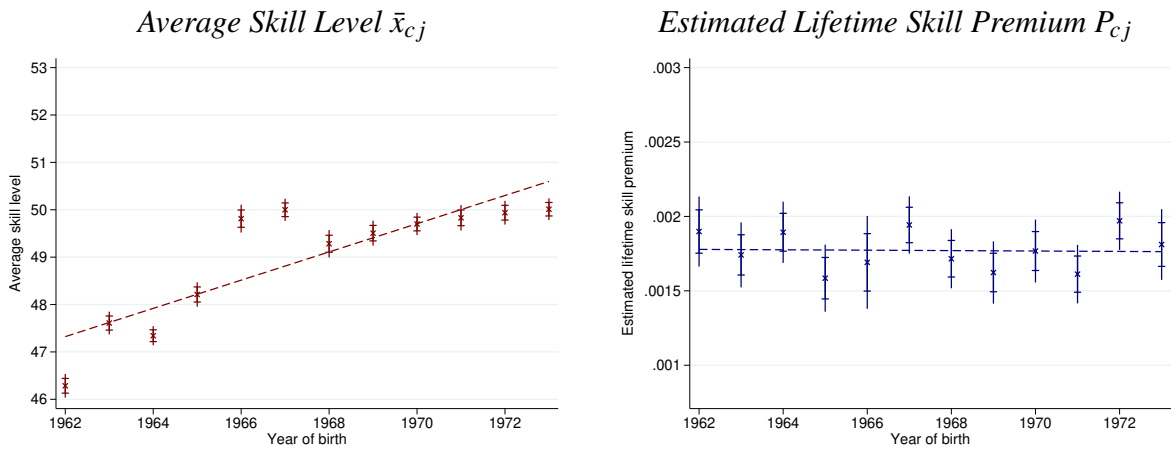
Panel A: Trends in Lifetime Skill Premia

	Enlistment data	Enlistment + survey data	
	Linear trend	OLS	IV
Change from 1967 to 1972 in lifetime premium to:			
Logical reasoning skill (P_{c1})	-0.000298	0.000622	0.002109
	(0.000040)	(0.000709)	(0.001870)
Vocabulary knowledge skill (P_{c2})	-0.000266	-0.000353	-0.001547
	(0.000042)	(0.000740)	(0.001903)
Number of individuals			
1967 cohort	42,427	2,927	2,927
1972 cohort	45,397	3,451	3,451

Panel B: Correlations in Skill Measures

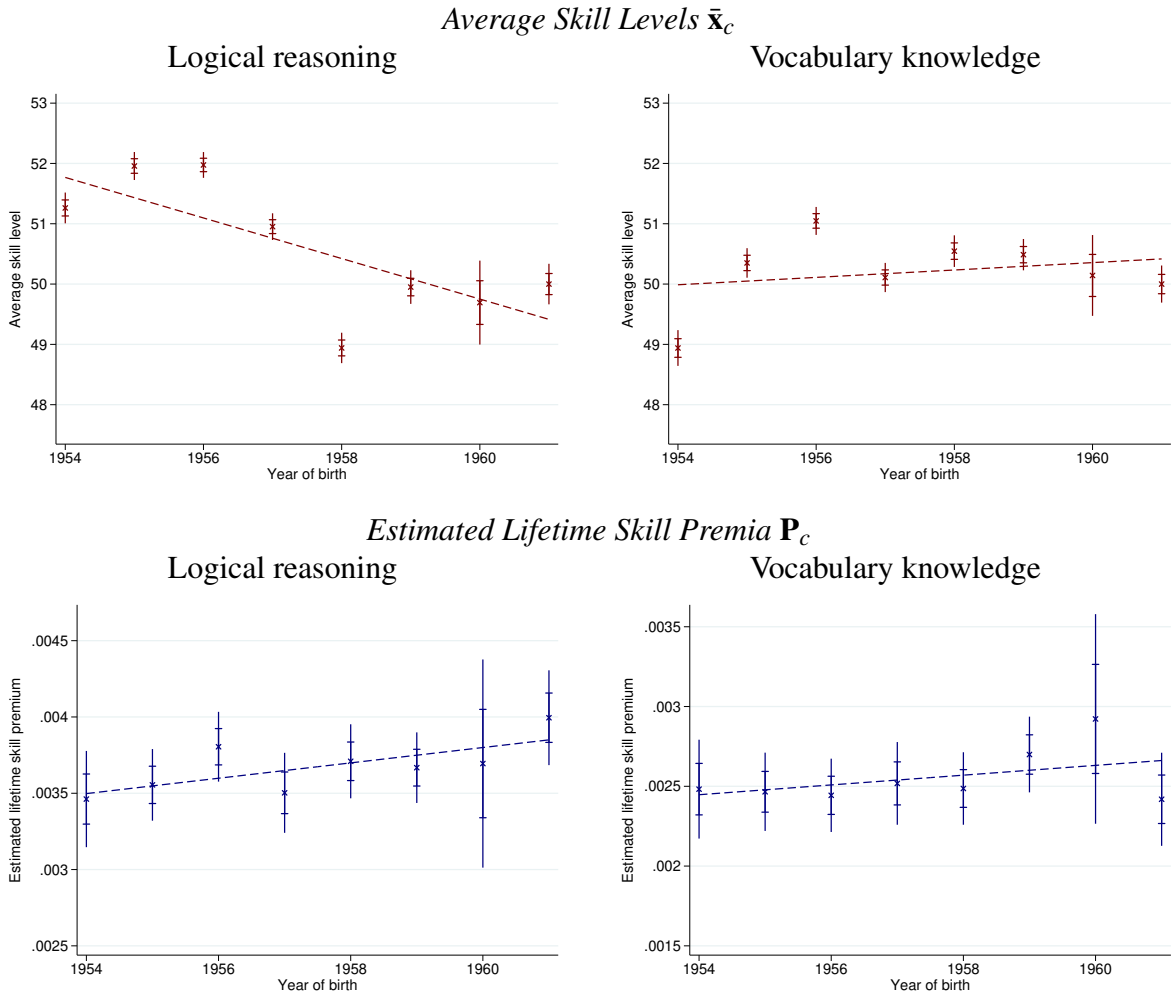
	Cohort		
	1967	1972	Difference
Correlation between survey and enlistment data in:			
Logical reasoning skill (x_{i1})	0.6557	0.6795	0.0237
	(0.0119)	(0.0085)	(0.0157)
Vocabulary knowledge skill (x_{i2})	0.6738	0.6910	0.0172
	(0.0106)	(0.0080)	(0.0129)
Number of individuals	2,927	3,451	

Notes. Panel A compares the estimated change in lifetime skill premia between birth cohorts 1967 and 1972 based on different estimation methods. The first column is based on the linear trend fitted to the series of estimated lifetime skill premia for the enlistment data, where tests were typically taken at age 18 or 19, as shown in Panel B of Figure I in the main text. The second and third columns are the differences between the lifetime skill premia for the two cohorts, as estimated on the set of individuals who have valid logical reasoning and vocabulary knowledge test scores in both the enlistment and survey data, where tests were typically taken at age 13. In the second (OLS) column, we estimate the lifetime skill premia for each cohort as the net present value of age-specific skill premia estimated via OLS, following the approach in Section IV.A in the main text. In the third (IV) column, we estimate the lifetime skill premia for each cohort as the net present value of age-specific skill premia estimated via IV, treating age-13 test scores as instruments for age-18/19 test scores. Panel B compares, between birth cohorts 1967 and 1972, the Pearson correlation of skills measured in the survey data with skills measured in the enlistment data. In both panels, standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates.



ONLINE APPENDIX FIGURE 1
Trends in Technical Knowledge and Technical Knowledge Premia Across Birth Cohorts 1962–1973, Military Enlistment Sample

Data are from the military enlistment sample for birth cohorts 1962–1973. We exclude birth cohorts 1974 and 1975 because of significant amounts of missing data on technical knowledge test scores for these cohorts. The left plot depicts the average technical knowledge skill $\bar{x}_{cj}$ for each birth cohort c. Skills are expressed as a percentile of the distribution for the 1967 birth cohort. The right plot depicts the estimated lifetime skill premium P_{cj} for technical knowledge for each birth cohort, constructed as described in Section IV.A in the main text. These skill premia are estimated controlling for logical reasoning and vocabulary knowledge skills. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence bands (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.



ONLINE APPENDIX FIGURE 2
Trends in Skills and Skill Premia across Birth Cohorts 1954–1961, Military Enlistment Sample

Data are from the military enlistment sample covering Swedish men born between 1954 and 1961 and who enlisted before 1980. For these birth cohorts, information on logical reasoning and vocabulary knowledge skills is based on scores from tests administered at military enlistment, called the Enlistment Battery 67. The first row of plots depicts the average skill $\bar{\mathbf{x}}_c$ for each birth cohort c. Skills are expressed as a percentile of the distribution for the 1961 birth cohort. The second row of plots depicts the estimated lifetime skill premia $\mathbf{P}_c$ for each birth cohort, constructed as described in Section IV.A in the main text. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence bands (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

Panel A: Consent Form



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Samtyckesblankett för Enkät-undersökning alt. Elektroniska val

Stockholms universitet är personuppgiftsansvarig för den behandling av personuppgifter som sker i Survey and Report.

Den lagliga grunden för behandlingen är att du gett samtycke till behandlingen i någon enkät.
För att projektet ska kunna utföras kommer ansvarig för studien och ansvarig för projektet ha tillgång till personuppgifterna. Uppgifterna kommer att behandlas så att inte obehöriga kan ta del av dem.

Om detta material bedöms ha ett bestående värde enligt de riktlinjer som anges i 6-8 §§ i RA-FS 1999:1 kommer det att bevaras för framtiden.

Enligt EU:s dataskyddsförordning samt nationell kompletterande lagstiftning har du rätt att:

återkalla ditt samtycke utan att det påverkar lagligheten av behandling som skett i enlighet med samtycket innan det återkallades,

begära tillgång till dina personuppgifter,

få dina personuppgifter rättade,

få dina personuppgifter raderade,

få behandlingen av dina personuppgifter begränsad.

Under vissa omständigheter medger dataskyddsförordningen samt kompletterande nationell lagstiftning undantag för dessa rättigheter, som kan komma att tillämpas.

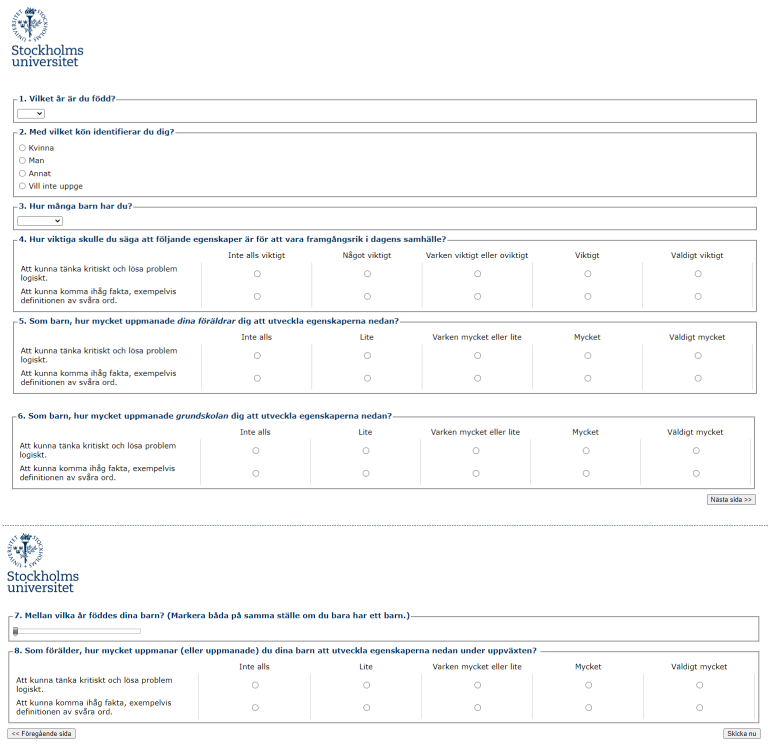
Om du vill åberopa någon av dessa rättigheter Kontakta Dataskyddsombudet vid Stockholms universitet (dso@su.se).

Mer information om detta finns på Datainspektionens hemsida. https://www.datainspektionen.se/

☐ Jag har läst och accepterar villkoren

Jag nekar samtycke — Jag samtycker

Panel B: Survey Form



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1. Vilket år är du född?

2. Med vilket kön identifierar du dig?
- Kvinna
- Man
- Annat
- Vill inte uppge

3. Hur många barn har du?

4. Hur viktiga skulle du säga att följande egenskaper är för att vara framgångsrik i dagens samhälle?

	Inte alls viktigt	Något viktigt	Varken viktigt eller oviktigt	Viktigt	Väldigt viktigt
Att kunna tänka kritiskt och lösa problem logiskt.	○	○	○	○	○
Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord.	○	○	○	○	○

5. Som barn, hur mycket uppmanade *dina föräldrar* dig att utveckla egenskaperna nedan?

	Inte alls	Lite	Varken mycket eller lite	Mycket	Väldigt mycket
Att kunna tänka kritiskt och lösa problem logiskt.	○	○	○	○	○
Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord.	○	○	○	○	○

6. Som barn, hur mycket uppmanade *grundskolan* dig att utveckla egenskaperna nedan?

	Inte alls	Lite	Varken mycket eller lite	Mycket	Väldigt mycket
Att kunna tänka kritiskt och lösa problem logiskt.	○	○	○	○	○
Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord.	○	○	○	○	○

Nästa sida >>

Stockholms universitet

7. Mellan vilka år föddes dina barn? (Markera båda på samma ställe om du bara har ett barn.)

8. Som förälder, hur mycket uppmanar (eller uppmanade) du dina barn att utveckla egenskaperna nedan under uppväxten?

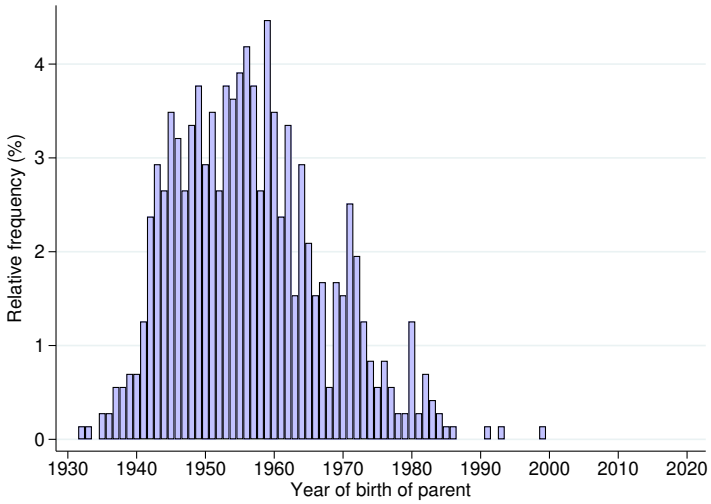
	Inte alls	Lite	Varken mycket eller lite	Mycket	Väldigt mycket
Att kunna tänka kritiskt och lösa problem logiskt.	○	○	○	○	○
Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord.	○	○	○	○	○

<< Föregående sida — Skicka nu

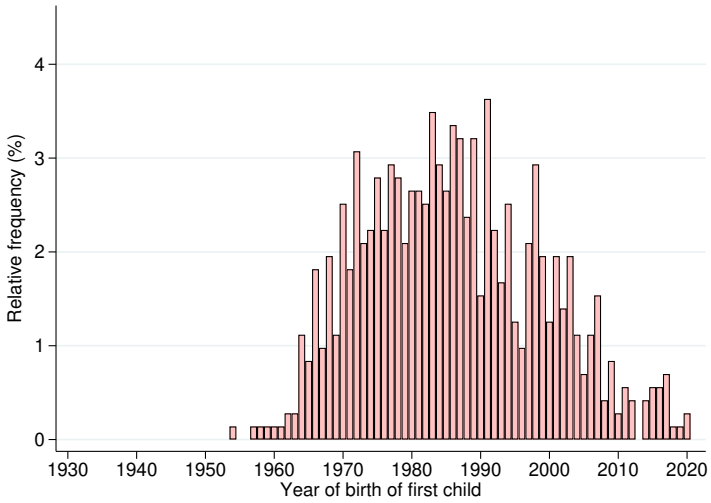
ONLINE APPENDIX FIGURE 3
Structure of the Survey of Parents' Perceptions

This figure shows the content and structure of the survey on parents' perceptions described in Section III.B in the main text. Panel A displays the consent form and Panel B displays the survey form, both in the original Swedish.

Panel A: Respondent

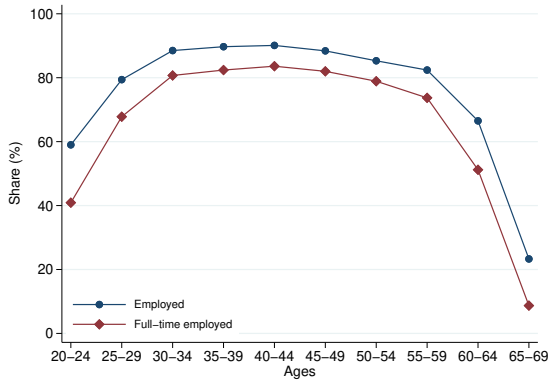


Panel B: Respondent's First Child

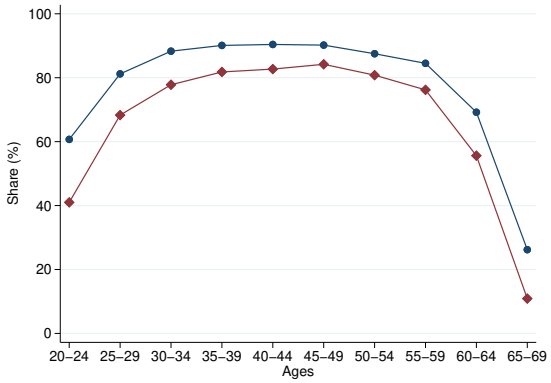


ONLINE APPENDIX FIGURE 4
Distributions of Year of Birth of Respondent and First Child in the Survey of Parents' Perceptions

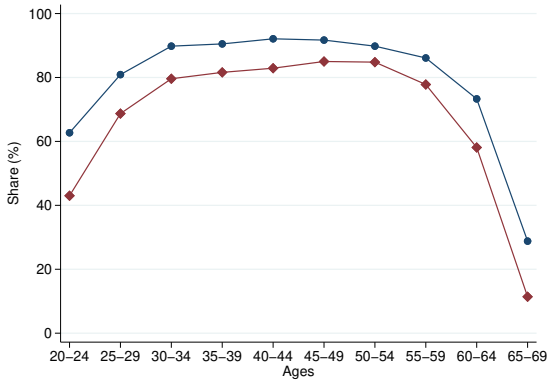
Data come from the survey of parents' perceptions described in Section III.B in the main text. Panel A shows the distribution of the year of birth of the respondent. Panel B shows the distribution of the year of birth of the respondent's first child.



(A) 2010



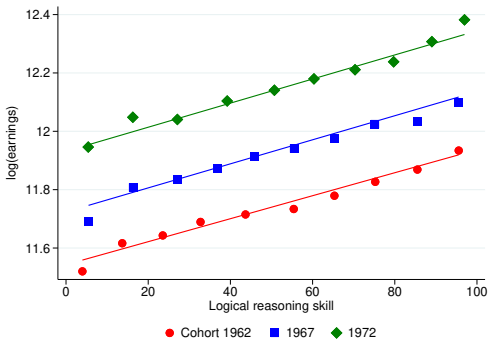
(B) 2015



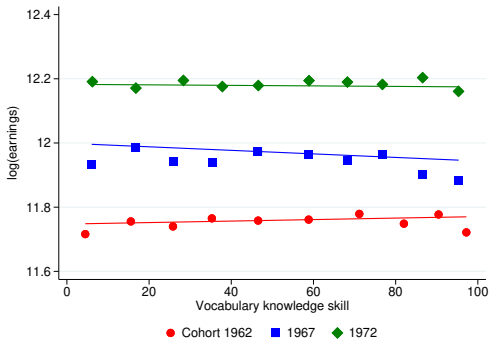
(C) 2019

ONLINE APPENDIX FIGURE 5
Male Employment Rates by Age Group for Selected Years

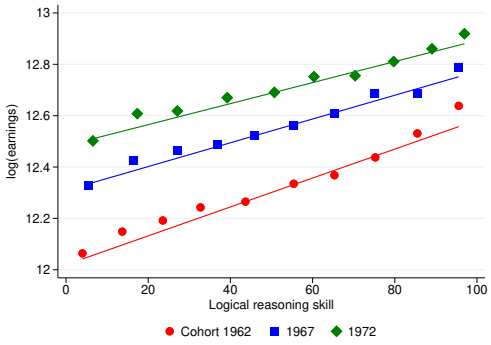
This figure shows the rates of employment and full-time employment among men in Sweden in 2010, 2015, and 2019, separately by age group, based on data from the Swedish Labour Force Surveys (Statistics Sweden 2020b). We define an individual as employed if he meets the definition of employment used by the International Labor Organization (see, e.g., Eurostat 2021). We define an employed individual as full-time employed if he reports working full-time in the survey.



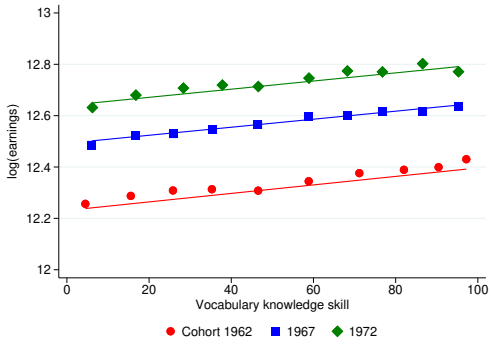
(A) Logical Reasoning, Age 30



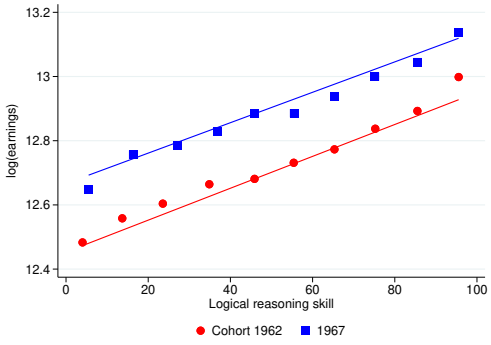
(B) Vocabulary Knowledge, Age 30



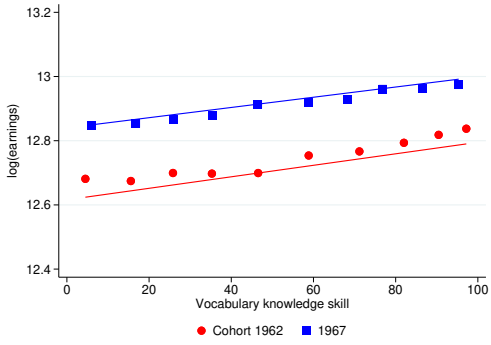
(C) Logical Reasoning, Age 40



(D) Vocabulary Knowledge, Age 40



(E) Logical Reasoning, Age 50

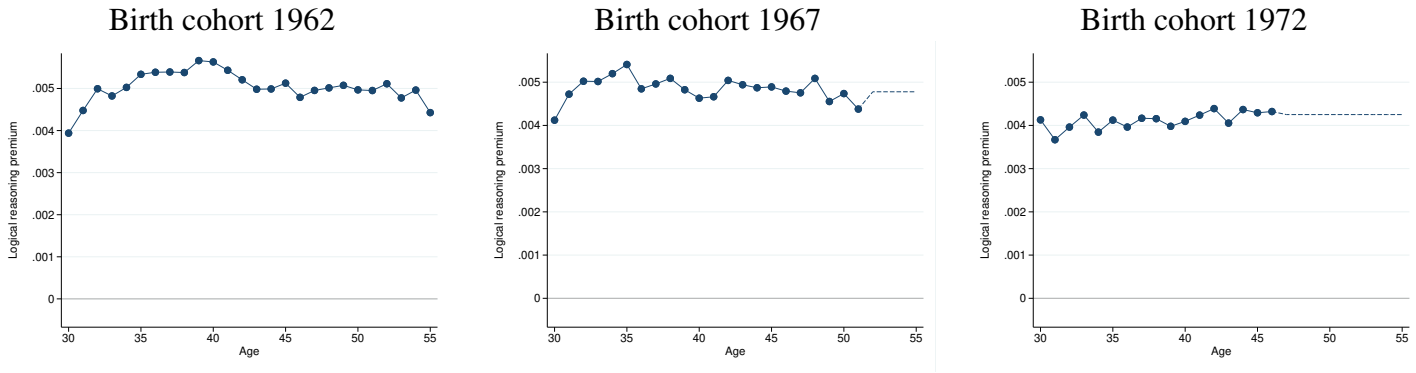


(F) Vocabulary Knowledge, Age 50

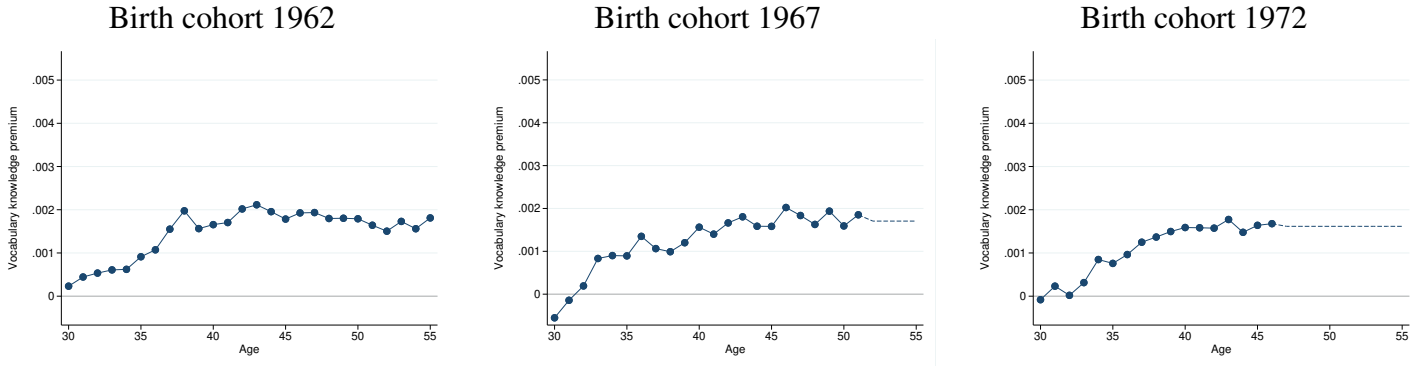
ONLINE APPENDIX FIGURE 6
Illustrating the Relationship Between Log(Earnings) and Skill Percentile, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. This figure illustrates the relationship between the mean of log annual earnings and logical reasoning and vocabulary knowledge skill for birth cohorts 1962, 1967, and 1972, at ages 30, 40, and 50. For each cohort, age, and skill dimension, we estimate a regression of log(earnings) on indicators for decile of skill. We plot the coefficients on the decile indicators, shifted by a constant so that their mean value coincides with the sample mean of log(earnings), against the average value of the given skill within the decile. We also plot a line whose slope is equal to the estimated premium $p_{c+a,a,j}$ of the given skill dimension, estimated from a regression of log(earnings) on skills $\mathbf{x}_i$, and whose intercept is chosen so that the line coincides with the decile coefficient at the fifth decile.

Logical Reasoning Skill Premium



Vocabulary Knowledge Skill Premium

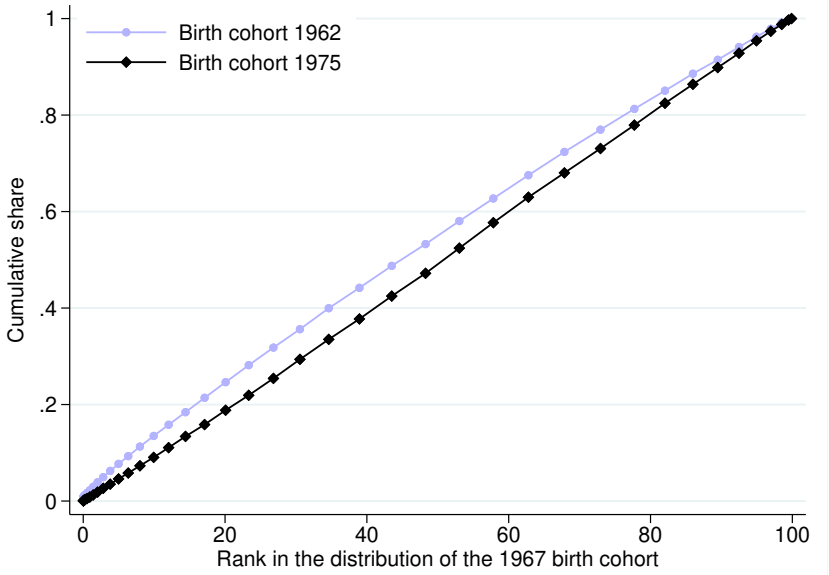


ONLINE APPENDIX FIGURE 7

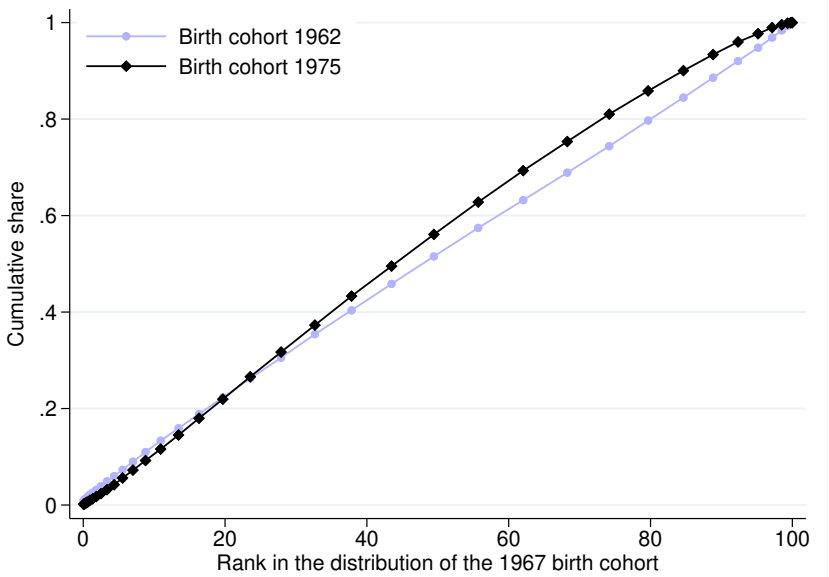
Illustrating the Extrapolation of Skill Premia to Ages with No Earnings Data, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plots illustrate how we estimate skill premia for ages of working life for which we do not observe earnings. The upper row of plots illustrates for logical reasoning and the lower row of plots illustrates for vocabulary knowledge. Each row includes plots for birth cohorts 1962, 1967, and 1972. For each cohort, we estimate the skill premia $\mathbf{p}_{c+a,a}$ in ages for which we do not observe earnings (dashed line) by taking the average estimated skill premia across all ages 40+ for which we do observe earnings (markers).

Logical Reasoning

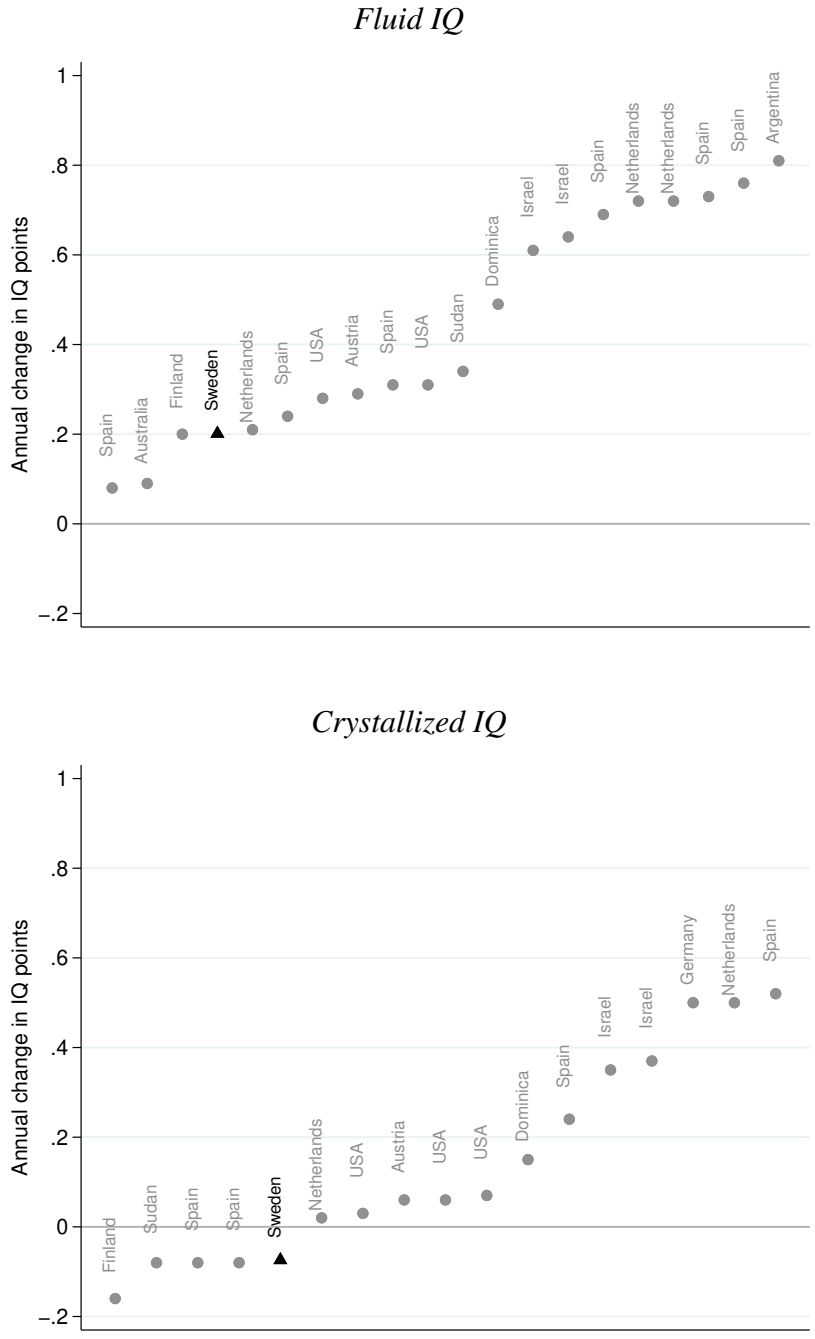


Vocabulary Knowledge



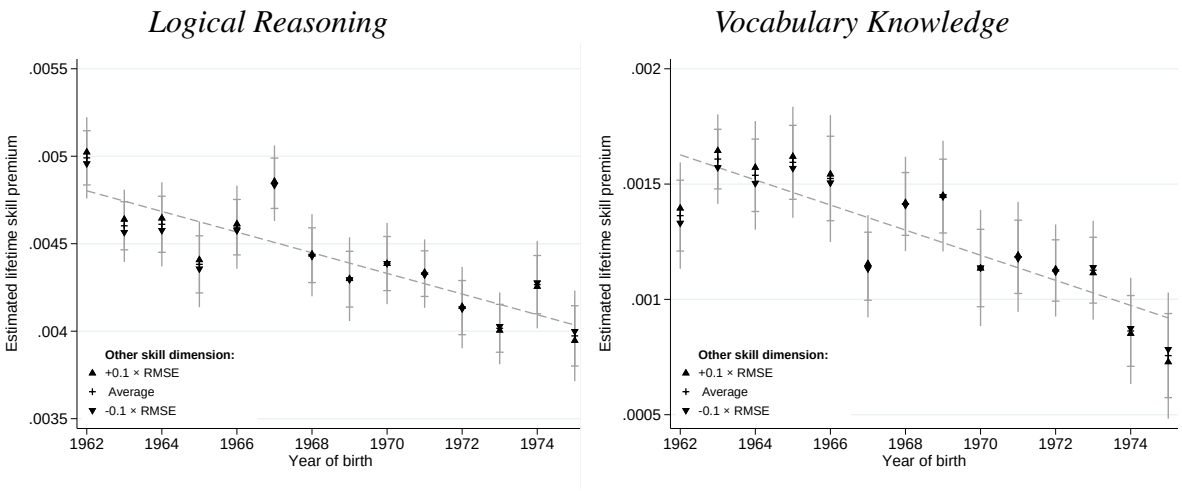
ONLINE APPENDIX FIGURE 8
Distributions of Skills in the 1962 and 1975 Birth Cohorts, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962 and 1975, with tests typically taken at age 18 or 19. Each plot depicts the empirical cumulative distribution function of skills x_{ij} for a given dimension j for members i of the 1962 and 1975 birth cohorts. Skills are expressed as a percentile of the distribution for the 1967 birth cohort.



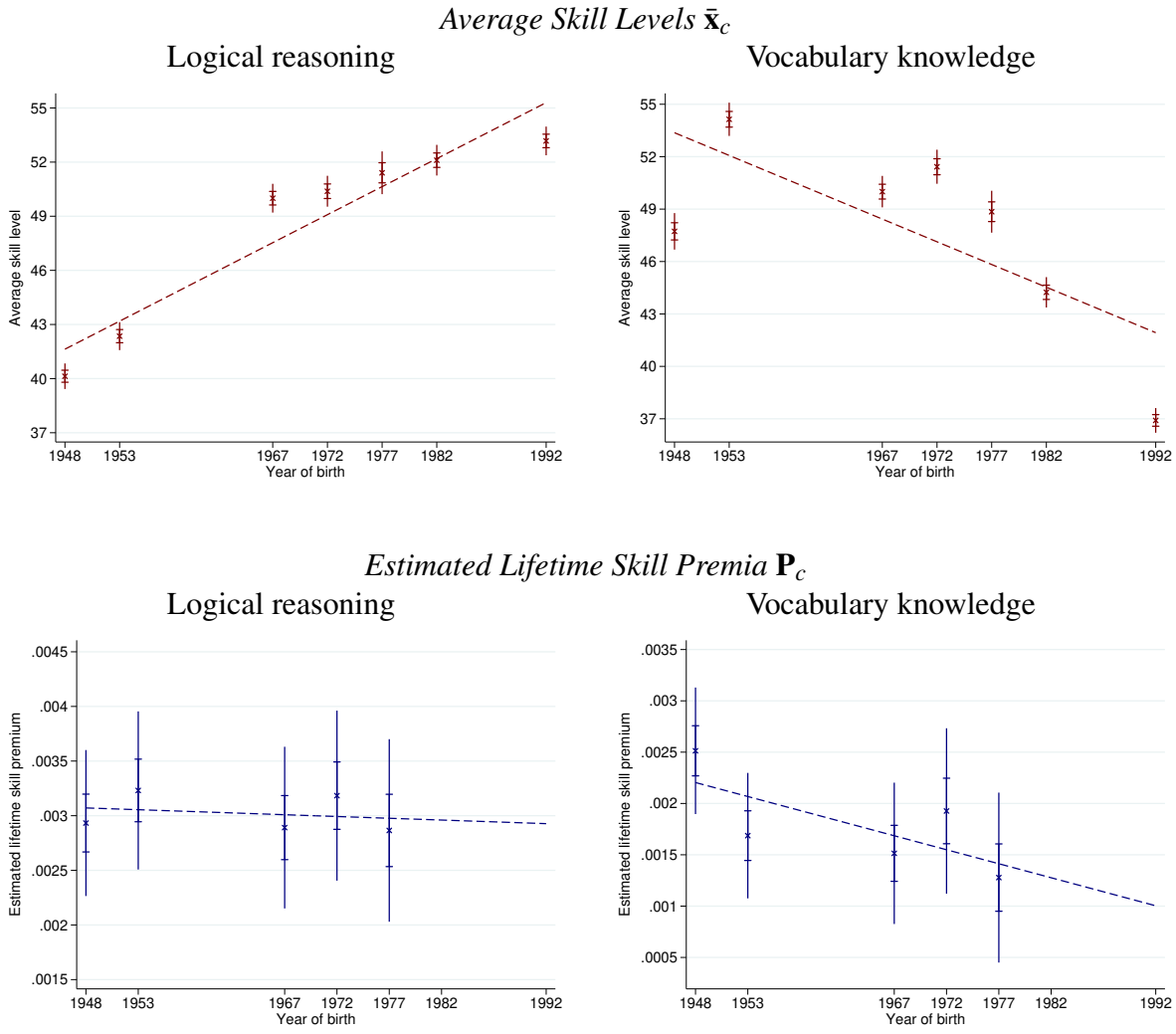
ONLINE APPENDIX FIGURE 9
Measured Trends in Fluid and Crystallized IQ

Data are from Pietschnig and Voracek (2015, Table S1, circles) or from the military enlistment sample covering birth cohorts 1962–1975 (triangles). We select from Pietschnig and Voracek's meta-analysis (2015, Table S1) all single-country studies of fluid or crystallized intelligence covering healthy adults with a sample size of at least 100 and a study period ending in 1980 or later. We classify studies of PIQ as fluid and studies of VIQ or verbal as crystallized. We plot the annual IQ gain in each study, labeling each study with the country in which the sample was obtained. For comparison, we also plot the annual IQ gain in the enlistment sample, which we calculate by standardizing the raw score on the logical reasoning (fluid) and vocabulary knowledge (crystallized) tests to have a mean of 100 and a standard deviation of 15 in the 1967 cohort.



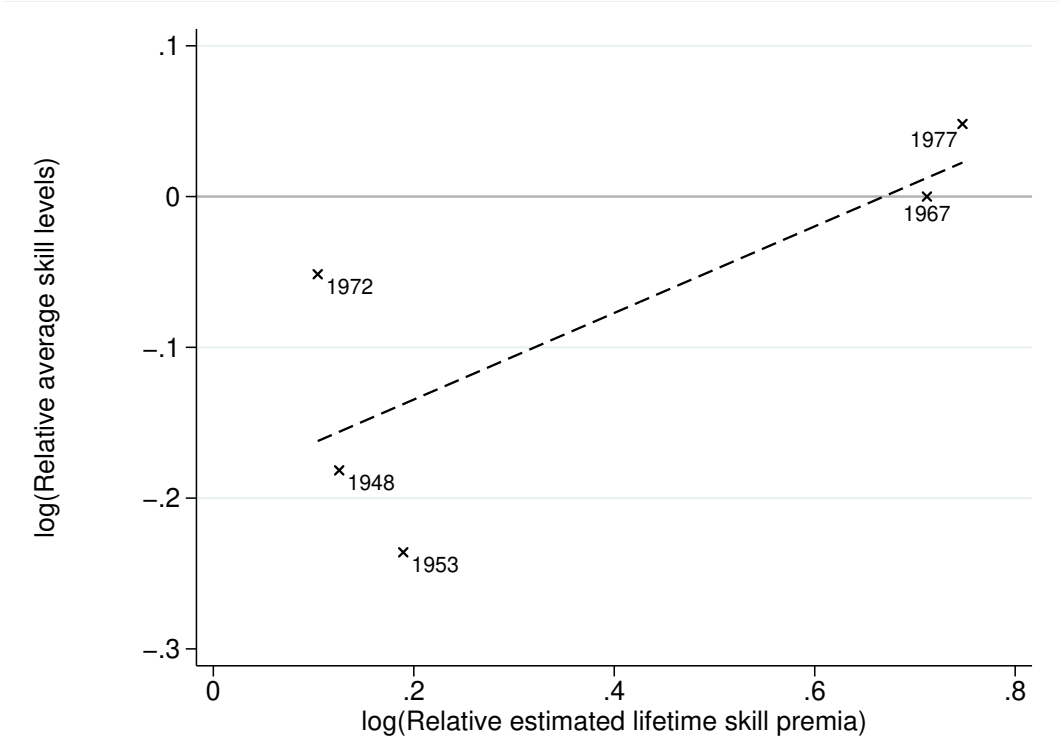
ONLINE APPENDIX FIGURE 10
Trends in Skill Premia across Birth Cohorts 1962–1975, Allowing for Interactions, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. We construct the plots as follows. For each cohort c and each year t for which we measure earnings, we estimate a generalization of equation (1) in the main text that includes an interaction $x_{i1}x_{i2}$ between the two skill dimensions. From these estimates we calculate cohort-and-year-specific skill premia for each skill dimension j, evaluated at three different levels of skill on the other dimension $j' \neq j$: the cohort average, 0.1 root mean squared error (RMSE) above the cohort average, and 0.1 RMSE below the cohort average, where the RMSE is calculated from a cohort-specific regression of skill $x_{ij'}$ on indicators for skill x_{ij}. We then follow the approach described in Section IV.A in the main text to estimate the cohort-and-year-specific premia for years outside of our sample, and we compute lifetime premia following equation (3) in the main text. For each dimension j, the plot depicts the lifetime premium for an individual in each cohort c whose skill on the other dimension $j' \neq j$ is equal to the cohort average ("Average"), an individual whose skill on the other dimension is 0.1 RMSE above the cohort average ("$+0.1 \times$ RMSE"), and an individual whose skill on the other dimension is 0.1 RMSE below the cohort average ("$-0.1 \times$ RMSE"). Each plot includes a line of best fit, 95 percent pointwise confidence intervals (inner grey intervals, marked by dashes), and uniform confidence bands (outer grey intervals, marked by line segments) corresponding to the "Average" series. Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019).



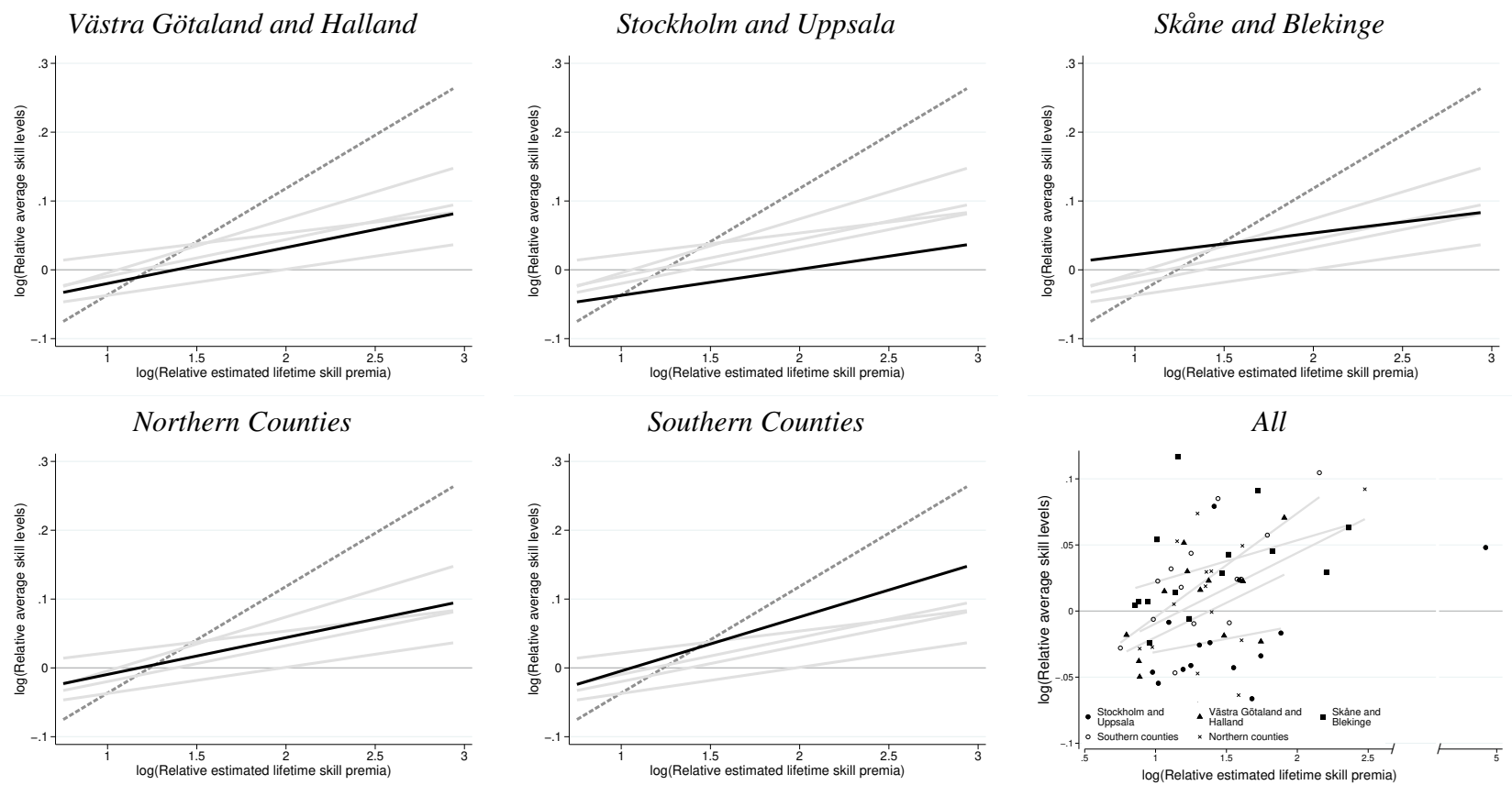
ONLINE APPENDIX FIGURE 11
Trends in Skills and Skill Premia across Birth Cohorts, Survey Sample

Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, 1977, 1982, and 1992. The first row of plots depicts the average skill $\bar{\mathbf{x}}_c$ for each birth cohort c. Skills are expressed as a percentile of the distribution for the 1967 birth cohort. The second row of plots depicts the estimated lifetime skill premia $\mathbf{P}_c$ for each birth cohort c in 1948, 1953, 1967, 1972, and 1977, constructed as described in Section IV.A in the main text. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence bands (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence bands are computed as sup-t bands following Montiel Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.



ONLINE APPENDIX FIGURE 12
Evolution of Relative Skill Levels and Relative Skill Premia, Women in Survey Sample

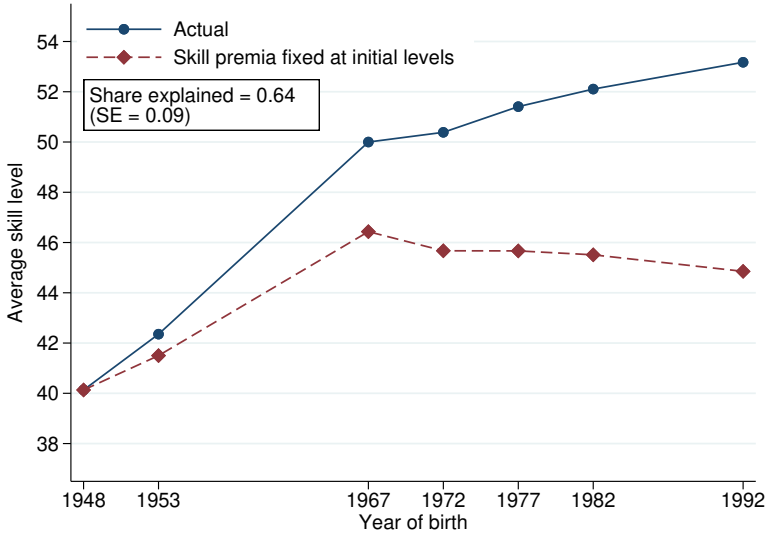
Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, and 1977, with tests typically taken at age 13, for female respondents. The plot shows a scatterplot of the natural logarithm of the relative average skill levels, $\ln\left(\frac{\bar{x}_{c1}}{\bar{x}_{c2}}\right)$, against the natural logarithm of the relative estimated lifetime skill premia, $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$. The dashed line depicts the line of best fit.



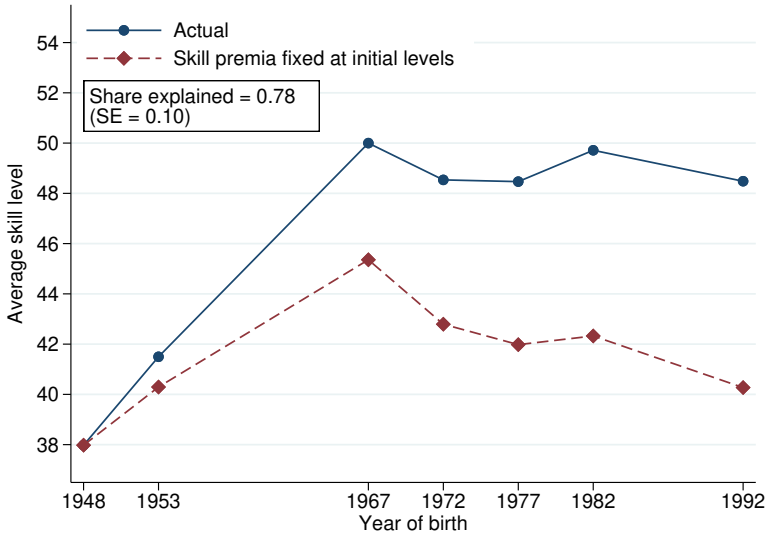
ONLINE APPENDIX FIGURE 13
Evolution of Relative Skill Levels and Relative Skill Premia by Region, Military Enlistment Sample

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The lower right plot shows a scatterplot of the natural logarithm of the relative average skill levels, $\ln\left(\frac{\overline{x}_{c1}}{\overline{x}_{c2}}\right)$, against the natural logarithm of the relative estimated lifetime skill premia, $\ln\left(\frac{P_{c1}}{P_{c2}}\right)$, separately by birth region. Each marker corresponds to a cohort and region. The light gray lines depict the lines of best fit for each region. Each of the other plots shows the line of best fit for the given region (black line), the lines of best fit for the other regions (light gray lines), and the line of best fit for the full sample (dashed line). We classify individuals into mutually exclusive and exhaustive regions according to their county of birth, excluding those born outside of Sweden, using data from Statistics Sweden (2016a). We classify Värmland, Örebro, Västmanland, Dalarna, Gävleborg, Västernorrland, Jämtland, Västerbotten, and Norrbotten as Northern counties, Södermanland, Östergötland, Jönköping, Kronoberg, Kalmar, and Gotland as Southern counties, and the remaining counties eponymously.

Men



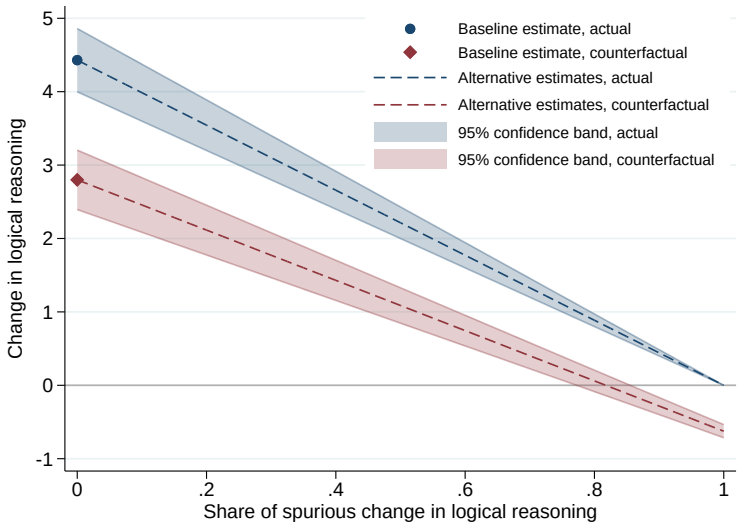
Women



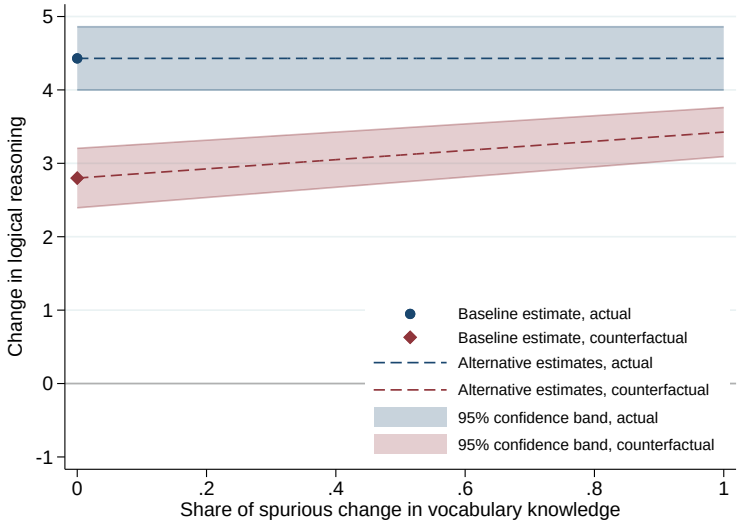
ONLINE APPENDIX FIGURE 14
Decomposition of Change in Average Logical Reasoning Skill, Survey Sample

Data are from the survey sample of male respondents (upper panel) and female respondents (lower panel) covering birth cohorts 1948, 1953, 1967, 1972, 1977, 1982, and 1992, with tests typically taken at age 13. Each plot depicts the average logical reasoning skill $\bar{x}_{c1}$ for each birth cohort c ("Actual") and the predicted average skill $\tilde{x}_{c1}\left(\overline{\mathbf{P}}_{\underline{c}}\right)$ under the counterfactual in which lifetime skill premia remain at the level estimated for the 1948 birth cohort ("Skill premia fixed at initial levels"). Skills are expressed as a percentile of the distribution for the 1967 birth cohort. We fit the model as in Figure IV in the main text, separately for men and women, taking the linear fit for the cohorts through 1977 (depicted for men in Online Appendix Figure 11) as our estimate of the lifetime skill premia $\mathbf{P}_c$ for all cohorts. The text box in each plot shows the estimated share $1-\frac{\tilde{x}_{\bar{c}1}\left(\mathbf{P}_{\underline{c}}\right)-\tilde{x}_{\underline{c}1}\left(\mathbf{P}_{\underline{c}}\right)}{\bar{x}_{\bar{c}1}-\bar{x}_{\underline{c}1}}$ of the observed change from 1948 through 1992 that is accounted for by changes in skill premia ("Share explained"). The standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. We exclude seven and three bootstrap replicates from the calculation of standard errors for the upper and lower plots, respectively, due to values inconsistent with the model.

Logical Reasoning

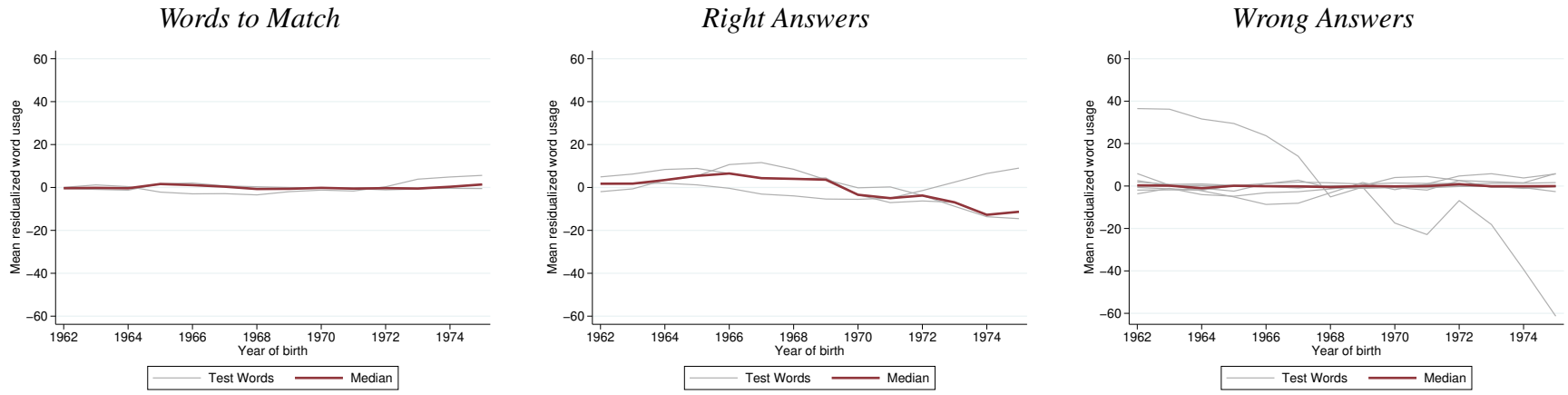


Vocabulary Knowledge



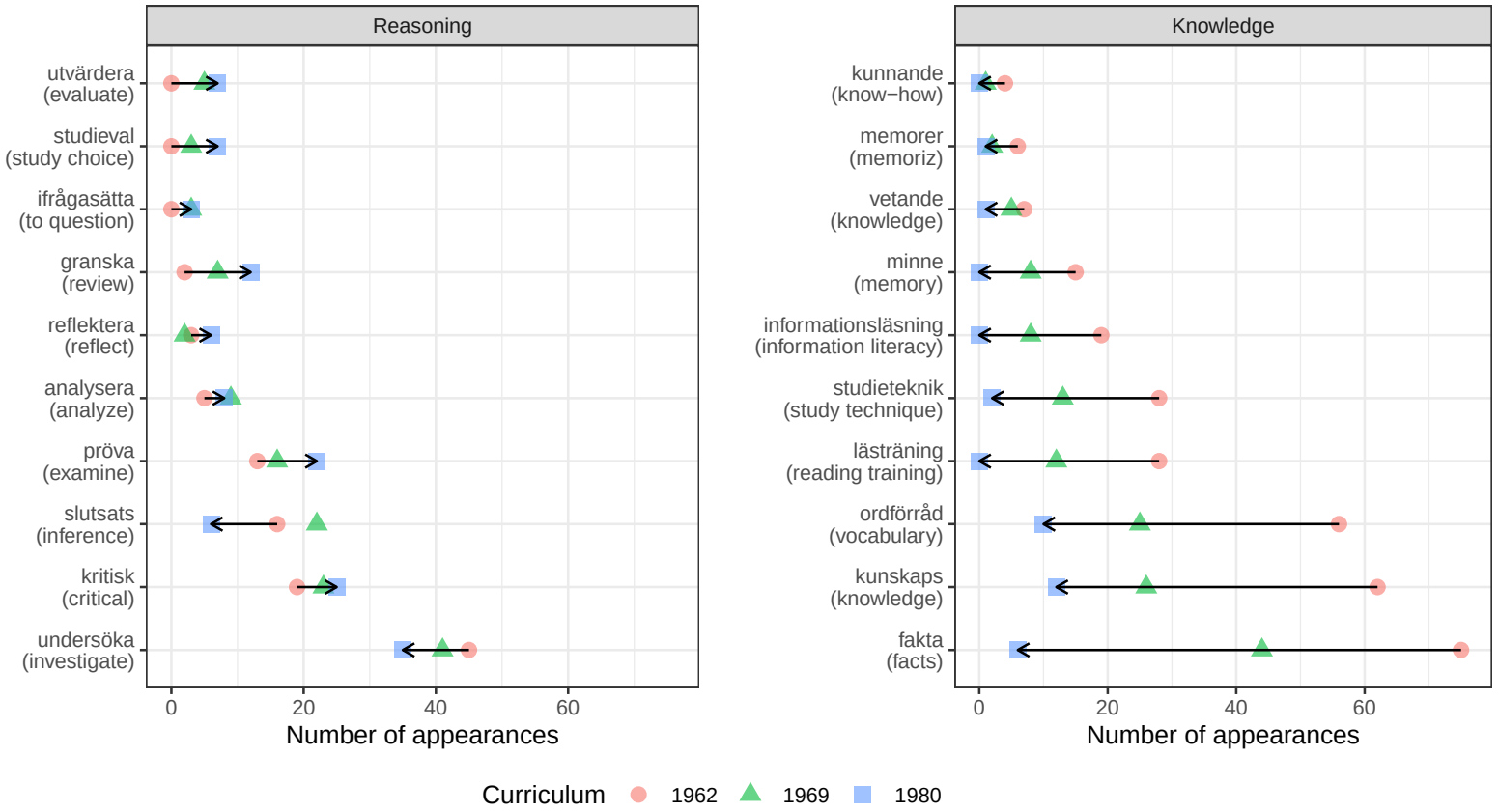
ONLINE APPENDIX FIGURE 15
Sensitivity to Spurious Cohort Trends in Skills

Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. To construct each plot, we assume that the true mean skill level $\tilde{x}_{\bar{c}j}$ on dimension j in the 1975 birth cohort $\bar{c}$ is given by $\omega_j \bar{x}_{\underline{c}j} + (1-\omega_j)\bar{x}_{\bar{c}j}$, such that $\omega_j \in [0,1]$ denotes the fraction of the observed change $\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$ that is spurious. We then re-estimate our model following the methods in Table I in the main text and calculate, for each ω_j, the implied actual change in logical reasoning skill $\tilde{x}_{\bar{c}1}(\mathbf{P}_{\bar{c}}) - \tilde{x}_{\underline{c}1}(\mathbf{P}_{\underline{c}})$ and the implied counterfactual change in logical reasoning skill $\tilde{x}_{\bar{c}1}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}1}(\mathbf{P}_{\underline{c}})$ if skill premia had remained constant at their level for the 1962 birth cohort. Each plot depicts the actual and counterfactual change in logical reasoning skill (y-axis) as a function of the fraction of the observed change that is spurious (x-axis). The upper plot depicts the implications of a spurious change in logical reasoning skill ($\omega_1 \in [0,1]$, $\omega_2 = 0$). The lower plot depicts the implications of a spurious change in vocabulary knowledge ($\omega_1 = 0$, $\omega_2 \in [0,1]$). For each depicted series, the shaded region collects pointwise 95% confidence intervals obtained via a nonparametric bootstrap with 50 replicates. The estimates labeled "Baseline estimate" correspond to the estimates in Panel A of Table I in the main text, i.e., the case in which $\omega_1 = \omega_2 = 0$.



ONLINE APPENDIX FIGURE 16
Trends in Usage of Words in Example Vocabulary Questions

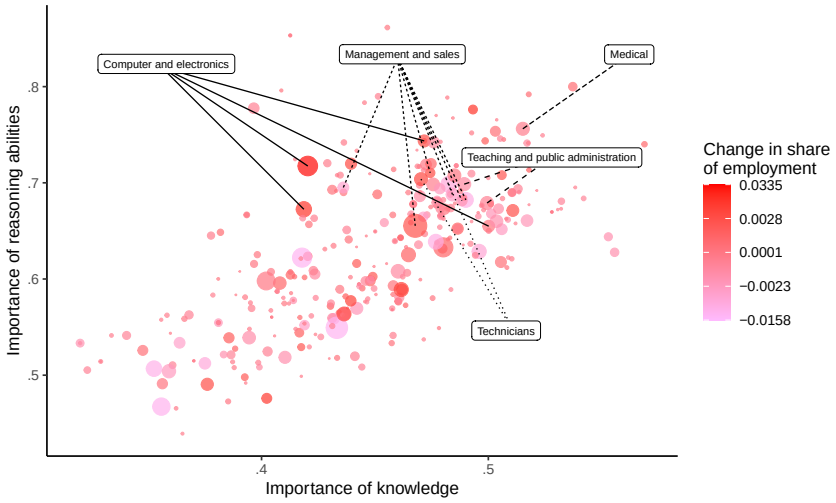
Data are from Kungliga biblioteket (2022). We construct the plots as follows. We begin with the example questions for Enlistment Battery 2000 posted at Rekryteringsmyndigheten (2010). We classify the words of interest in the example synonym questions (Rekryteringsmyndigheten 2012) into the words the test-taker is asked to match to a synonym ("words to match"), the correct synonyms ("right answers"), and the incorrect synonyms ("wrong answers"). We specify a set of reference words consisting of the names of the days of the week. From Kungliga biblioteket (2022) we obtain the frequency with which each word of interest, as well as each reference word, was used in the newspaper *Dagens Nyheter* in each year from 1962 to 1993. For each word of interest we estimate a regression of the frequency of the word's use on the total frequency across all reference words, where the unit of observation is the word-year. We take the residual from this regression and compute, for each word of interest and each birth cohort 1962–1975, the average residual over the first 19 years of the cohort's life. We subtract the mean of this series and take the result as our measure of the cohort's exposure to the given word of interest. In each plot, each lighter line shows the exposure of each cohort to a given word of interest, and the darker line shows the median exposure of each cohort across all words of interest in the given category. We use example questions for Enlistment Battery 2000 because we are not aware of example questions for Enlistment Battery 1980 that are in the public domain.



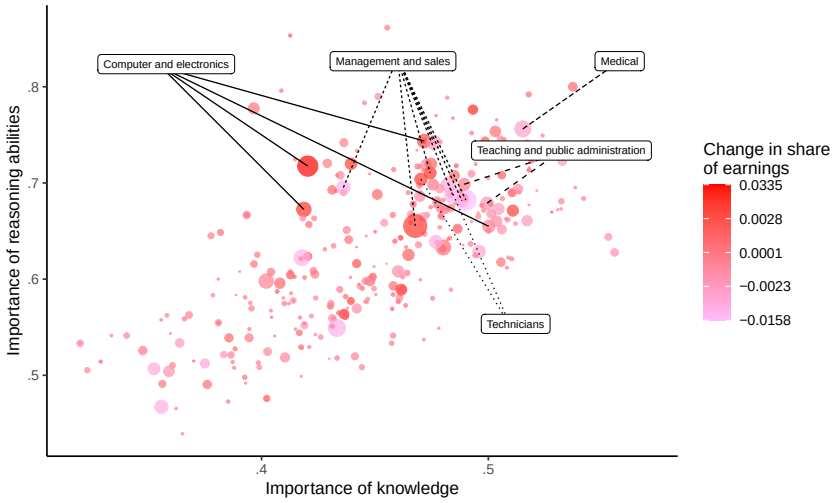
ONLINE APPENDIX FIGURE 17
Selected Word Families Related to Reasoning vs. Knowledge in Swedish Primary School Curricula

The plot shows the number of appearances of selected word families related to fluid intelligence ("Reasoning", left panel) and crystallized intelligence ("Knowledge", right panel) in the 1962, 1969, and 1980 revisions of the Swedish primary school Curricula (Läroplan for grundskolan; Skolöverstyrelsen 1962, 1969, 1980). Translations of word families are in parenthesis under the original Swedish. In both panels, word families are listed in ascending order based on their number of appearances in the 1962 Curriculum. The arrows point from the number of appearances in the 1962 Curriculum to the number of appearances in the 1980 Curriculum. We chose a set of keywords based on a close reading of the Curricula and categorized them in word families. We counted the number of appearances of each word family as follows. For the "analysera," "granska," "ifrågasätta," "informationsläsning," "kunnande," "ordförråd," "pröva," "reflektera," "slutsats," "studieval," and "utvärdera" families, we searched for all words that start with the same characters. For the "fakta," "kritisk," "kunskaps," "memorer," "minne," "undersöka," and "vetande" families, we searched for all words that start with the same characters plus a few alternate forms. For the "lästräning" and "studieteknik" families, we searched for the exact word only. We conducted searches automatically. A Swedish speaker then reviewed search results and excluded cases, such as negations, where usage did not match our intent.

Panel A: Changes in Shares of Total Employment



Panel B: Changes in Shares of Total Earnings



ONLINE APPENDIX FIGURE 18
Growth of Occupations in Sweden by Their Reasoning and Knowledge Intensity

The figure shows scatterplots of the knowledge and reasoning intensity as well as growth of each occupation in the Swedish Occupational Register. Panel A measures occupation growth with the change in the occupation's share of total employment between cohorts 1962 and 1975, with marker sizes proportional to the occupation's share of total employment in cohort 1962. Panel B measures occupation growth with the change in the share of total earnings between cohorts 1962 and 1975, with marker sizes proportional to the occupation's share of total earnings in cohort 1962. In both panels, the y-axis depicts the total importance of reasoning abilities, and the x-axis depicts the total importance of knowledge. We measure the distribution of employment and earnings across occupations in the Swedish Occupational Register using data on employment histories from 2004 onwards from Statistics Sweden (2021), using 4-digit Swedish Standard Classification of Occupations 96 (SSYK 96) codes, and taking each individual's occupation to be the one observed in the available year closest to the year the individual turns 40. For each O*NET 25.0 (2020) occupation we define the total importance of reasoning abilities by summing the importance scores of Inductive, Deductive, and Mathematical Reasoning abilities and dividing by the highest possible sum. Similarly, we define the total importance of knowledge by summing the importance scores of all knowledge categories and dividing by the highest possible sum. We compute the total importance of reasoning abilities and knowledge of each SOC 2010 occupation by taking unweighted averages across all corresponding occupations in O*NET 25.0 (2020). We match the occupations in the Swedish Occupational Register to occupations in the Standard Occupational Classification 2010 (SOC 2010) by using the crosswalks from Statistics Sweden (2016c) and BLS (2015), manually excluding some matches to improve accuracy. We define the total importance of reasoning abilities and knowledge for each occupation in the Swedish Occupational Register by taking employment-weighted averages across all corresponding SOC 2010 occupations, using May 2018 OES employment estimates (BLS 2019) as weights. Heuristic descriptions, written by us, are applied to all occupations with total importance of reasoning above 0.65 and a share of earnings in 1962 of least 0.01. This figure includes information from the O*NET 25.0 Database by the U.S. Department of Labor, Employment and Training Administration (USDOL/ETA). Used under the CC BY 4.0 license. O*NET® is a trademark of USDOL/ETA. We have modified all or some of this information. USDOL/ETA has not approved, endorsed, or tested these modifications.

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