Labor Market Returns and the Evolution of Cognitive Skills: Theory and Evidence

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Abstract

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 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 social security earnings records, 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 35 percent of the measured increase in reasoning skill, and can also explain the decline in knowledge. An original survey of parents and a review of trends in school curricula show evidence of increasing emphasis on reasoning as compared to knowledge.

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1 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 et al. 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 et al. 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] The existing cognitive science literature emphasizes factors, such as improvements in health and nutrition, that expand the supply of skill (e.g., Pietschnig and Voracek 2015; Rindermann et al. 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 paper, 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 typically at age 18 or 19) and earnings (collected for the social security system over the lifecycle) 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 both 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 return to dif-

[1] Rindermann et al. (2017) write, "Among the most discussed topics in intelligence research is the rise of average IQ test results across generations in the 20th century" (p. 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." (p. 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).

ferent skills. In our model, the relative returns to different skills can be recovered from a Mincerian regression of the log of earnings on test scores in a cross-section of individuals, even in the presence of unmeasured determinants of earnings that are correlated with the market value of individuals' skill endowments.

We parameterize the model so that a single unknown parameter governs the degree to which individuals 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 4.6 percentile points relative to the distribution in the 1967 cohort. The estimated lifetime earnings premium to an additional 10 percentile points of logical skill fell by 0.07 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 2.7 percentile points. The estimated lifetime premium to an additional 10 percentile points of verbal skill also 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 performance fell along with its market return, suggesting a decline in the demand for this skill dimension. Moreover, the *relative* premium to vocabulary knowledge fell by more than 40 percent. Seen through the lens of our model, the declining relative premium to crystallized intelligence drives a reallocation of effort towards developing abstract reasoning and away from acquiring knowledge. Thus, the model predicts an increase in logical reasoning and a decrease in vocabulary knowledge due to changes in labor market returns.

We can 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 verbal knowledge performance would have increased by 3.0 and 3.2 percentile points, respectively. The estimated model thus implies that trends in labor market returns explain 35 percent of the growth in logical reasoning performance, and more than fully explain the decline in verbal reasoning performance.

We extend our baseline analysis in a few directions. First, we use a nationally representative survey linked to earnings records to extend our analysis to a broader set of birth cohorts, from 1948 to 1977, and to skills measured at a younger age. We find that the relative level of and return to logical reasoning performance rose across these cohorts, though our estimates are less precise than those from the (much larger) enlistment sample. Second, we adjust the trends in levels of and returns to skills for measured covariates such as height and secondary school completion. Although adjusting for covariates is conceptually delicate, as some covariates may themselves respond to the labor market skill premia, we find broadly similar conclusions across a variety of sensitivity analyses.

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. A review of pedagogical scholarship suggests similar trends in school curricula in Sweden, which are explicitly designed to meet the needs of work and society. We view this evidence as consistent with the mechanism underlying our estimated model.

Our analysis has some important limitations. One is that we treat the skill demand portion of the model fairly abstractly and do not offer an account of why some skills have become relatively more valuable in the labor market over time. A second limitation is that, while we explore sensitivity to accounting for several measured covariates, our conclusions require assumptions on unmeasured determinants of earnings and skills. These assumptions do not require that skills are uncorrelated with unmeasured determinants of earnings or that labor market returns are uncorrelated with unmeasured determinants of skill investment, but are nevertheless substantive, and we discuss their plausibility in light of prior evidence in the body of the paper. A third limitation is that we focus on the labor market returns to skills and do not measure their nonmarket returns. However, we show that our conclusions are preserved if market and non-market returns to skill move in proportion across cohorts. A final limitation is that, due to the nature of the military enlistment data that we use, our analyses are limited to men only.

The main contribution of this paper 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 non-cognitive skills (see, for example, the review by Sanders and Taber 2012 and recent papers by Roys and Taber 2020 and 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, e.g., 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 et al. (1998) develop a general-equilibrium model of the supply and demand for skill. Their model is richer than ours in its treatment of 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 different measures of ability or intelligence. Although some work in this literature considers the possibility that social demands may affect the development of skills, we are not aware of work in this literature that quantifies trends in the returns to different types of skills, or that uses an estimated model to link trends in returns to trends in measured skills.[6]

Much prior work studies trends in skills and their returns,[7] including some work using linked administrative data from elsewhere in Europe,[8] as well as some work using the same data from Sweden that we use.[9] Rönnlund et al. (2013) report trends in test scores in Sweden from 1970–1993. Lindqvist and Vestman (2011) study the labor market return to cognitive and non-cognitive skills in Sweden. Especially related, Edin et al. (forthcoming) estimate trends in the returns to cognitive and non-cognitive skills in Sweden. None of these papers uses an estimated economic

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

[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, p. 79) notes that "When society asks us to increase our use of any skill over time, the brain responds," and cites research by Maguire et al. (2006) on the effect of occupational demands on brain structure in the context of London taxi and bus drivers.

[7]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 US between the 1980s and 2000s.

[8]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. 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.

[9]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).

model to quantify the role of labor market returns in driving cohort trends in multidimensional skills.[10]

The remainder of the paper is organized as follows. Section 2 presents our model and approach to identification. Section 3 describes the data we use. Section 4 presents our findings. Section 5 concludes.

2 Model

2.1 Production and Earnings

There is a population of workers $i \in \{1,...,N\} = \mathcal{N}$, each of which is associated with a cohort $c(i) \in \{\underline{c},...,\overline{c}\}$. Each worker is characterized by a skill level $\mathbf{x}_i \in \mathbb{R}^J_{\geq 0}$ for $J \geq 2$.

In each time period t each worker i has an experience level $a(i,t) = t - c(i)$ and an effective labor supply $z_{it} \in \mathbb{R}_{\geq 0}$, where $z_{it} > 0$ if $a(i,t) \in \{1,...,A\}$ 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 after which workers in that cohort enter the labor force.

Let $\mathbf{X}_t$ be the $J \times A$ matrix whose a^{th} column is given by the sum of $z_{it}\mathbf{x}_i$ over all workers i with experience level $a(i,t) = a$. 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.[11]

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.

[10] Lindquist (2005) models trends in the demand for skill in Sweden arising from capital-skill complementarity.

[11] That is, the a^{th} 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

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

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

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

where $\nabla F_{t,a}$ is the gradient of $F_t\left(\mathbf{X}_t\right)$ at $\mathbf{X}_t$ with respect to the a^{th} column of $\mathbf{X}_t$. We will assume that $\nabla F_{t,a(i,t)}^{'} \mathbf{x}_i > 0$ for all workers i in all periods t of working life.

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

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

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

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

We can write the preceding as

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

where $B_{t,a}$ is a scalar, $\mathbf{p}_{t,a}$ is a vector of skill premia, and both of these are specific to a time period and experience level.[12]

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

[12] Specifically,

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

2.2 Skill Investment

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

$$\begin{aligned} \mathbf{x}_i &\geq \mu_i \\ S_{c(i)}\left(\mathbf{x}_i - \mu_i\right) &\leq \overline{S}_{c(i)} \end{aligned} \tag{2}$$

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 the individual endowment μ_i as representing cross-sectional differences within a cohort, say in ability or access to schooling, while the budget $\overline{S}_c$ can be seen as representing the total time and effort available for skill investment. Trends across cohorts in the function $S_c(\cdot)$ can be interpreted as representing broad changes in the skill formation technology, 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.[13] Because we take the timing of entry into the labor market as given, we do not account for any foregone 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 utility 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 lifecycle, $\left\{\mathbf{p}_{c(i)+a,a}\right\}_{a=1}^{A}$.[14] 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 (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

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

[14] Appealing to a large market, we assume that each worker i neglects any effects of his own skill investment on $B_{t,a}$ and $\mathbf{p}_{t,a}$.

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 (3) with its expectation.[15]

The worker's problem is also equivalent to maximizing $\mathbf{P}'_{c(i)}\tilde{\mathbf{x}}_i$ subject to $\tilde{\mathbf{x}}_i \geq 0$ and $S_{c(i)}\left(\tilde{\mathbf{x}}_i\right) \leq \overline{S}_{c(i)}$, where $\tilde{\mathbf{x}}_i = \mathbf{x}_i - \mu_i$. The solutions to this problem depend only on the cohort $c\left(i\right)$ of the worker and not on the worker's identity. In this sense, within-cohort variation in skill arises only due to variation in the individual skill endowment μ_i. We further assume that μ_i has mean zero within each cohort. This assumption is without loss of generality since we can always define $\mathbf{x}_i$ and μ_i relative to a cohort-specific mean endowment.[16]

2.3 Parameterization and Identification

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

$$S_c\left(\tilde{\mathbf{x}}\right) = \left(\sum_j K_{cj}^{\rho-1}\left(\tilde{x}_j\right)^{\rho}\right)^{\frac{1}{\rho}}$$

where $\mathbf{K}_c \in \mathbb{R}^J_{>0}$ is a vector that we may think of as describing the cost of increasing skill along each of the J dimensions for cohort c. Here $\rho > 1$ 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 $c\left(i\right) = c\left(i'\right)$. Therefore write $\tilde{\mathbf{x}}_c = \tilde{\mathbf{x}}_c\left(\mathbf{P}_c\right)$ as the optimal $\tilde{\mathbf{x}}_i$ for all workers i in cohort c. Here $\tilde{\mathbf{x}}_c\left(\cdot\right)$ is a skill supply function that

[15] That is, taking $\mathrm{E}_c\left[\cdot\right]$ 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] 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 $\mathring{\mathbf{x}}_i \geq \mathring{\mu}_i$ and $S_{c(i)}\left(\mathring{\mathbf{x}}_i - \mathring{\mu}_i\right) \leq \overline{S}_{c(i)}$ is equivalent to the problem of maximizing $\mathbf{P}'_{c(i)}\mathbf{x}_i$ subject to (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.

returns the cohort's optimal skill investment given the cohort's lifetime skill premia $\mathbf{P}_c$.[17] 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 $j = 2$. Under the model, the relative supply of fluid intelligence obeys

$$\ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{c2}}\right) = \frac{1}{\rho-1}\ln\left(\frac{P_{c1}}{P_{c2}}\right) - \ln\left(\frac{K_{c1}}{K_{c2}}\right). \tag{4}$$

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*

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

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

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

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 (4). 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.

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.

[17] Specifically, for each skill $j \in \{1, \ldots, J\}$, we have

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

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 $\{(\alpha\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\overline{c}}$, where the scalar $\alpha > 0$ may be unknown.*

Corollary 1 allows that the econometrician may understate or overstate the lifetime skill premia, provided the error is proportional across dimensions j. An immediate implication is that if there are non-market returns to skill that move in proportion to market returns, 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 discounted present value of cohort-and-period-specific skill premia $\mathbf{p}_{t,a} = \mathbf{p}_{t,t-c}$. We identify these skill premia, 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*

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

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

Assumption 2 allows that the unobserved determinants of earnings are linearly related both to the observed covariates $\mathbf{d}_{it}$ and to the market value of the skill endowment $\mathbf{p}_{t,t-c}^{'}\mu_i$.

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,*

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

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

Importantly, Proposition 2 does not require that all determinants of earnings are observed, or that unobserved determinants of earnings are independent of skills. Rather, Proposition 2 requires that unobserved determinants of earnings are related to the skill endowment through its market value, and with a coefficient that does not vary over time.

Although we identify $\mathbf{P}_c$ only up to an unknown multiple $\alpha > 0$, going forward we will for simplicity write as if $\alpha = 1$. Moreover, although for concreteness Assumption 2 requires that $\tilde{\alpha} \geq 0$, 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.

2.4 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 the relative skill mix that would have occurred in the absence of changes in relative skill premia.[18]

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.[19] 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.[20]

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.[21] In our empirical analysis,

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

[19] 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.

[20] 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, pp. 253-254).

[21] Say that $\frac{P_{\overline{c}1}}{P_{\overline{c}2}} > \frac{P_{\underline{c}1}}{P_{\underline{c}2}}$. If $\frac{1}{\overline{c}-\underline{c}-1} \sum_{c=\underline{c}}^{\overline{c}-1} \left[\ln\left(\frac{K_{c+1,1}}{K_{c+1,2}}\right) - \ln\left(\frac{K_{c1}}{K_{c2}}\right)\right] > 0$, then our construction will understate the elasticity of

we explore the sensitivity of our findings 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, thus allowing us to look at the evolution of skills at different points in a person's schooling.

Assumption 2 is violated if there are unmeasured factors that directly affect earnings and are more strongly correlated with the endowment of one skill dimension than the other. Especially problematic are factors that lead us to misestimate the trends in the relative return to different skill dimensions across cohorts. In our empirical analysis, we explore the sensitivity of our findings to including proxies for candidate factors in the covariate set $\mathbf{d}_{it}$.

3 Data

3.1 Linked Data on Test Scores and Earnings

Our main analysis uses data on scores from tests administered at military enlistment (Enlistment Battery 80), typically at age 18 or 19, for the near-population of Swedish men born between 1962 and 1975 and who enlisted in 1980 or later. Carlstedt (2000), Rönnlund et al. (2013), and Gyllenram et al. (2015) describe these tests, which were unchanged over this period, in more detail.

To extend our analysis to a broader set of birth cohorts, we also 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 percent of the birth cohorts 1948, 1953, 1967, 1972, and 1977.[22] Härnqvist (1998) and Svensson (2011) describe the survey and tests in more detail. We include only males in our analysis.

Both data sources include tests for logical reasoning and vocabulary knowledge. 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 $(j = 2)$. Both data sources also include a test of spatial reasoning. Appendix Table 3 shows how our results change when we combine logical and spatial scores into a single composite measure of fluid intelligence. For completeness, Appendix Figure 1 shows trends in the level of and premium for technical skills, which are measured in the enlistment data but not in the survey data, and Appendix Figure 2 shows trends in the level of and premia for skills in the military enlistment data

substitution $\frac{1}{\rho-1}$. If $\frac{1}{\bar{c}-\underline{c}-1}\sum_{c=\underline{c}}^{\bar{c}-1}\left[\ln\left(\frac{K_{c+1,1}}{K_{c+1,2}}\right)-\ln\left(\frac{K_{c1}}{K_{c2}}\right)\right] < 0$, then our construction will overstate it.

[22] We exclude the 1982 birth cohort due to limited follow-up data on earnings.

for men born between 1954 and 1961, for which the format of the tests was different.

In the enlistment data, the logical reasoning test consisted of drawing correct conclusions based on statements that are made complex by distracting negations or conditional clauses and numerical operations (Carlstedt and Mårdberg 1993; Gyllenram et al. 2015). The vocabulary knowledge test consisted of correctly identifying synonyms to a set of words (Gyllenram et al. 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).

We merge both sets of test scores to data on labor market earnings for the universe of Swedish workers from the Income and Tax Register (Statistics Sweden 2014a, 2014b). Our measure of w_{it} is the total labor market earnings of a man i in a year t.

We include in our analysis only those individuals for whom we measure both logical reasoning and vocabulary knowledge scores.[23] For each data source and each dimension j, we let x_{ij} denote the percentile rank of individual i's score within the distribution of scores of those born in 1967. 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. Appendix Table 1 shows the number of observations for each birth cohort for each data source.

3.2 Original Survey of Parents' Perceptions

We conducted an original survey to assess the importance 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

[23] We drop rare cases where one of these scores exceeds the allowable range.

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.

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

4 Results

4.1 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. Appendix Figure 5 shows that full-time work is highest during these years. Appendix Table 3 shows how our findings change when we alter the beginning or ending year of working life.

We estimate the parameter $\mathbf{p}_{t,a}$ in equation (1) by ordinary least squares regression of the log of total earnings $\ln(w_{it})$ on the vector of percentile ranks $\mathbf{x}_i$, separately for each worker 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 $c + a \leq T$, for T the most recent year of earnings data available. 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. Appendix Figure 7 illustrates this extrapolation for three example cohorts. Appendix Table 3 shows how our findings change when we average over a shorter or longer span of ages.

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 $c \in \{\underline{c}, ..., \overline{c}\}$. Appendix Table 3 shows how our findings change when we vary the assumed value of δ. We obtain standard errors for $\mathbf{P}_c$ via a nonparametric bootstrap in which we sample individuals i with replacement.

Figure 1 depicts the average skill levels $\bar{\mathbf{x}}_c$ and the estimated lifetime skill premia $\mathbf{P}_c$ across cohorts in the enlistment data along with their 95 percent uniform confidence intervals. For convenience we label cohorts with their birth year, i.e., $c-29$. Figure 1 also depicts the lines of best fit through the data. In the case of the estimated lifetime skill premia, a Wald test does not reject the linear fit ($p = 0.0812$ for logical reasoning, $p = 0.2903$ for vocabulary knowledge).

The top row of plots in Figure 1 shows that logical reasoning skill rose, on average, by 4.6 rank points, relative to the 1967 distribution, across the birth cohorts from 1962 to 1975. By contrast, vocabulary knowledge skill fell, on average, by 2.7 rank points. The bottom row of plots in Figure 1 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 rank point of logical reasoning skill fell from 0.0048 to 0.0041 across the birth cohorts from 1962 to 1975, and that the lifetime premium for a rank point of verbal reasoning skill fell from 0.0016 to 0.0009. Thus, the lifetime premium for both skill dimensions fell, with a proportionately much greater decline for vocabulary knowledge.[24]

Figure 2 depicts the evolution of the relative skill levels $\ln(\bar{x}_{c1}/\bar{x}_{c2})$ and of the relative lifetime skill premia $\ln(P_{c1}/P_{c2})$ across the two dimensions. Figure 2 shows that these objects both 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 (4). Figure 3 shows that a similar qualitative pattern obtains in our survey sample, which is smaller and for which estimates are noisier. Appendix Figure 8 depicts the underlying estimates of skill levels and lifetime skill premia in the survey sample.

To address the possibility of measurement error, Appendix Table 4 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 0 and also include the slope of the linear fit from Figure 1. Relative to the slope of the linear fit from Figure 1, 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.

[24]Prior work finding evidence of declining returns to cognitive skill includes Castex and Dechter (2014) for the US, Markussen and Røed (2020) for Norway, and Edin et al. (forthcoming) for Sweden.

4.2 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 $\overline{\mathbf{x}}_c$ in each cohort as our estimate of $\tilde{\mathbf{x}}_c$. We take the linear fit in Figure 1 as our estimate of the lifetime skill premia $\mathbf{P}_c$.[25] 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. Appendix Table 3 shows how our findings change when we use a quadratic fit and when we do not smooth premia at at all.

Appendix Table 2 shows that we estimate an elasticity of substitution of $\frac{1}{\rho-1} = 0.344$ with a standard error of 0.135. Appendix Figure 9 illustrates the implications of the model by depicting a scatterplot of the form in Figure 2 overlaid with the relative supply curve in (4) defined by the estimated skill supply function $\tilde{\mathbf{x}}_{\underline{c}}(\cdot)$ for the 1962 birth cohort.

Figure 4 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 3.0 rank points instead of 4.6 as in the actual data. Vocabulary knowledge skill rises by 3.2 rank points rather than falling by 2.7 rank points. In this sense, according to the model, changes in the lifetime skill premia $\mathbf{P}_c$ account for 34.6 percent of the increase in logical reasoning skill (with a standard error of 1.8 percent), and for more than the entire decline in vocabulary knowledge skill.

4.3 Sensitivity to Controls

We explore the sensitivity of our conclusions to adjusting for covariates. We adjust both the estimated trend in mean skills $\overline{\mathbf{x}}_c$ and the estimated trend in lifetime skill premia $\mathbf{P}_c$. 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 and normalizing $\mathbf{d}_i$ to have mean zero in the 1967 birth cohort.[26] 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 covariates $\mathbf{d}_{it}$ in the time-and-age-specific earnings regressions from which we estimate $\mathbf{p}_{t,a}$.

[25] Consistent with the regularity condition in Proposition 1, based on the linear fit we reject the hypothesis that $\ln\left(P_{\underline{c}1}/P_{\underline{c}2}\right) = \ln\left(P_{\overline{c}1}/P_{\overline{c}2}\right)$ at conventional significance levels ($p < 0.001$).

[26] Within the model in Section 2, we may think of this exercise as re-normalizing the skill endowment μ_i to have cohort-specific mean $\Gamma\overline{\mathbf{d}}_c$ where $\overline{\mathbf{d}}_c$ is the cohort-specific mean of $\mathbf{d}_i$ and Γ is a matrix whose j^{th} row contains the coefficients on $\mathbf{d}_i$ in the regression of skills x_{ij} on cohort indicators and covariates $\mathbf{d}_i$.

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 $\mathbf{P}_c$, then these 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. 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 5 shows how our findings change when we adjust for age at enlistment, an indicator for having completed secondary school at age 18, log(height) and log(weight), and a measure of non-cognitive skills taken at the time of enlistment. Across these exercises, we find that changes in labor market returns consistently account for at least 25 percent of the increase in logical skill, and for more than the entire decline in vocabulary knowledge skill.

4.4 Trends in Emphasis among Parents and Schools

Across successive birth cohorts, we observe a decline in the relative premium to crystallized intelligence as compared to fluid intelligence. A premise of our model is that skill investments respond to these changing market incentives. Here we explore whether the main actors involved in children's skill acquisition—parents and schools—changed which skills they emphasize in a manner consistent with responding to changing market incentives.

Panel A of Figure 5 depicts trends in the perceived importance of different skills among parents, as reported in the survey described in Section 3.2. Parents of more recent birth cohorts place 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 skills in today's society, how much their own parents emphasized each skill, and how much their own primary school emphasized each skill. We find some 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.

We can also investigate changes in school curricula over the period we study. We focus on primary schooling because Figure 3 suggests that the trends 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,[27] 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.[28]

Scholars of pedagogy in Sweden have noted a trend in the Curricula towards 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" (p. 2015). Similar trends have been observed in other areas of study.[29] These trends seem consistent with a greater emphasis on reasoning as compared to knowledge,[30] though we note that, in our survey, parents' perceptions of their own primary schooling experience do not reflect such a trend (see Panel B of Figure 5).

5 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 towards greater emphasis on reasoning relative to knowledge among parents and schools.

[27]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" (p. 13). The 1980 Curriculum repeats this language, quoting it as part of the Education Act (p. 13).

[28]For example, the 1962 Curriculum partly reflected the findings from systematic interviews of supervisors and employees regarding the knowledge demands of the workplace (Thavenius 1999, p. 43; Statens Offentliga Utredningar 1960:15, pp. 500-508).

[29]Löfdahl (1987) studies the physics curriculum but also describes a more general evolution from 1962 to 1980 towards more emphasis on creativity and critical thinking (see also Johansson and Wickman 2012, p. 199). Prytz (2015, p. 317) studies the mathematics curriculum and notes a trend since the 1960s towards less emphasis on performing calculations. Dahlbäck and Lyngfelt (2017, p. 167-168) study the evolution of the Swedish curriculum and note that, compared to the 1969 Curriculum, the 1980 Curriculum places greater emphasis on the creative use of language.

[30]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 only Sweden (see, e.g., Darling-Hammond et al. 2020).

We conclude that it is fruitful to incorporate market-driven incentives into the analysis of cohort trends in measured intelligence.

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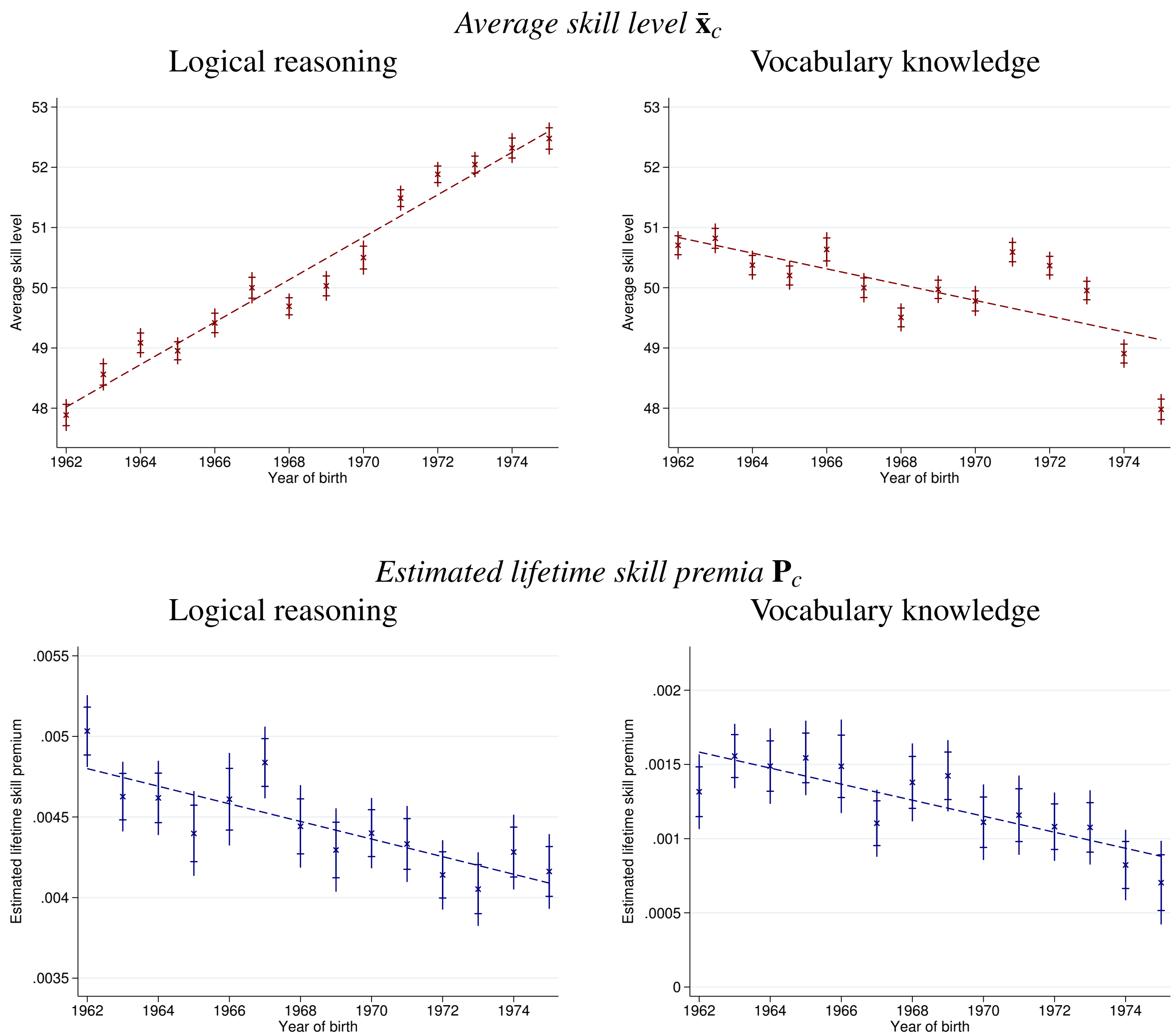
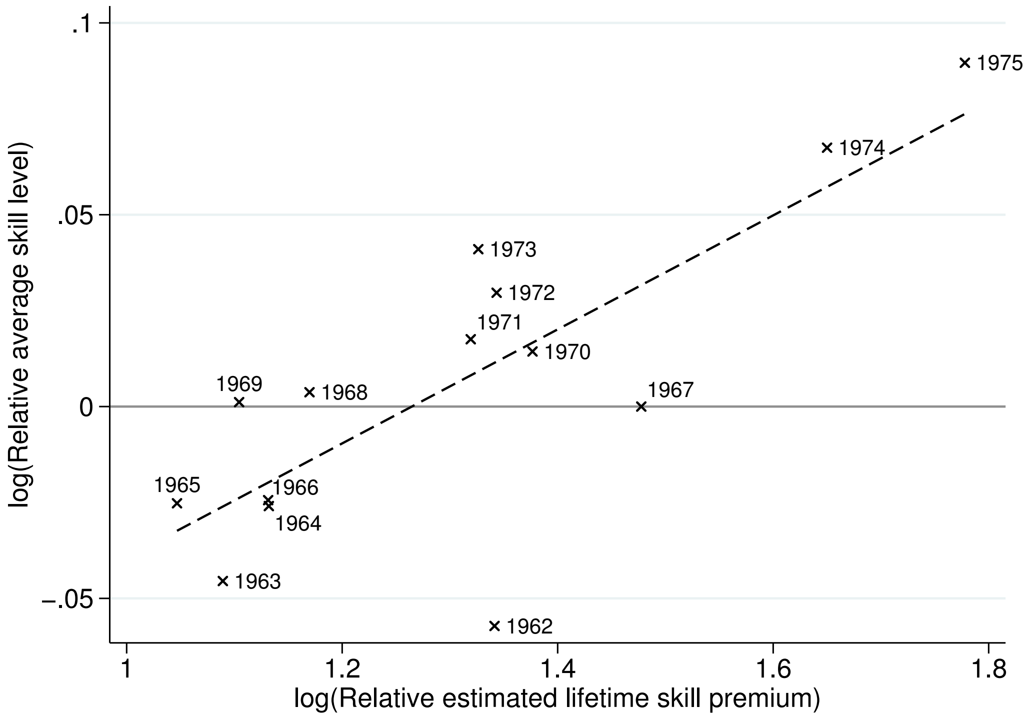
Figure 1: Trends in skills and skill premia across birth cohorts 1962–1975, military enlistment data



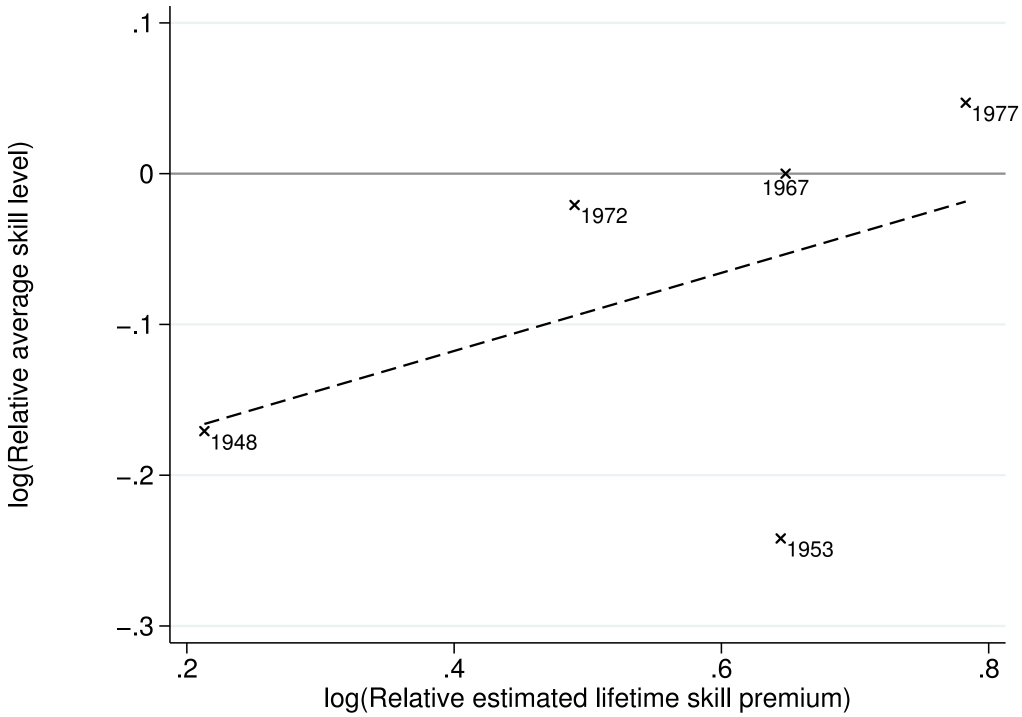
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The first row of plots depicts the average skill $\bar{\mathbf{x}}_c$ for each birth cohort c. Skills are expressed as a percentile of the distribution for the 1967 birth cohort. The second row of plots depicts the estimated lifetime skill premia $\mathbf{P}_c$ for each birth cohort, constructed as described in Section 4.1. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence intervals (outer intervals, marked by line segments). Pointwise confidence intervals are based on standard errors from a nonparametric bootstrap with 50 replicates. Uniform confidence intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

Figure 2: Evolution of relative skill levels and relative skill premia, military enlistment sample



Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative estimated lifetime skill premia, $\ln(P_{c1}/P_{c2})$. The dashed line depicts the line of best fit.

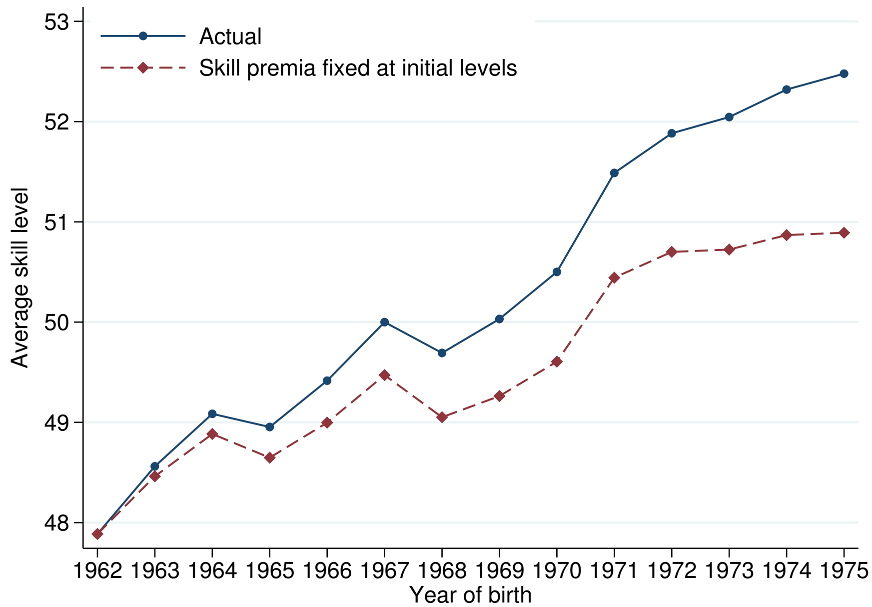
Figure 3: Evolution of relative skill levels and relative skill premia, survey sample



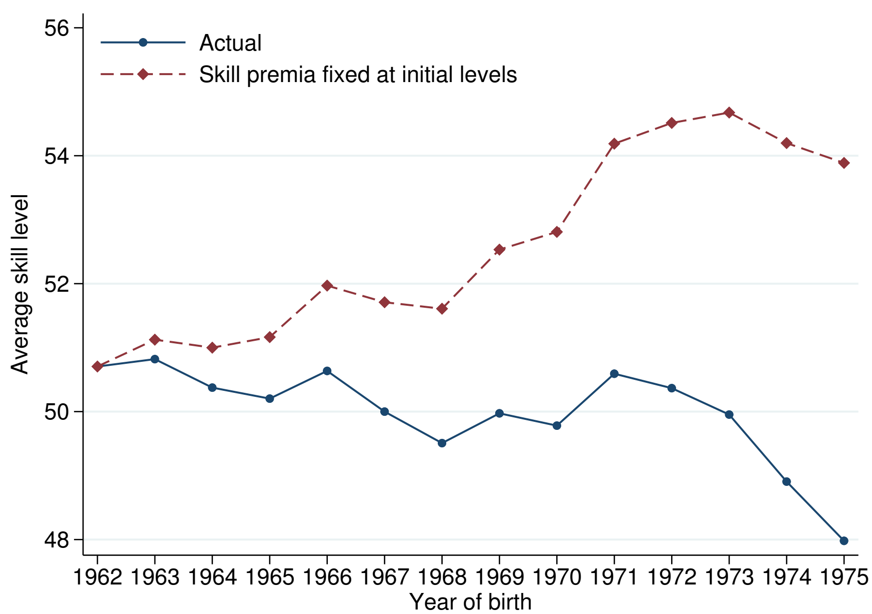
Notes: Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972 and 1977, with tests typically taken at age 13. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative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

Figure 4: Decomposition of change in average skill level, military enlistment data

Logical reasoning



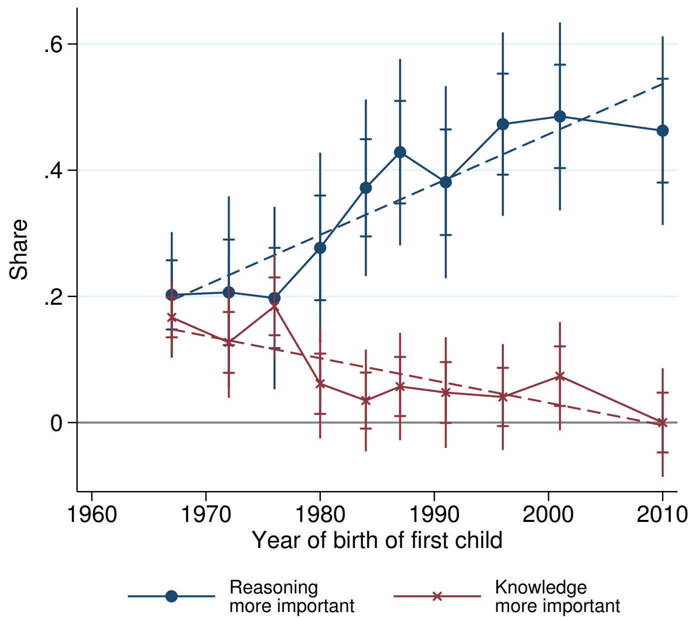
Vocabulary knowledge



Notes: 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 $\tilde{\mathbf{x}}_c\left(\mathbf{P}_{\underline{c}}\right)$ 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.

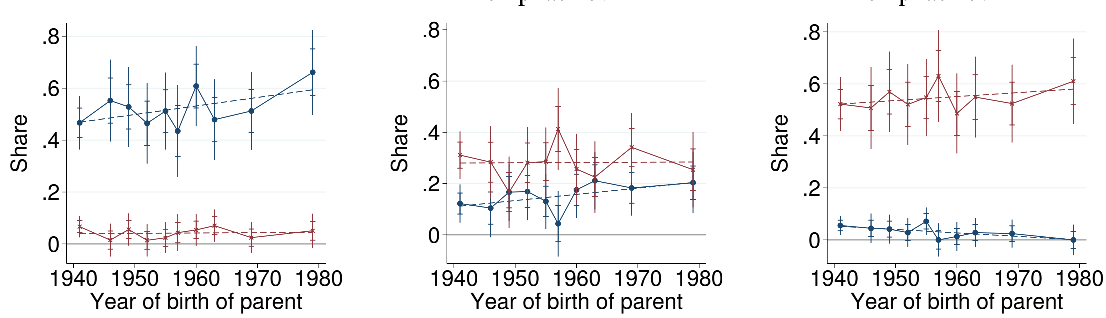
Figure 5: Trends in the perceived importance of different skills in the survey of parents' perceptions

Panel A: Which skill did parents encourage more in their own children?



Panel B: Other measures of importance

Which is important today? | Which did own parents emphasize? | Which did own primary school emphasize?



Notes: Data come from the original survey of parents' perceptions described in Section 3.2. Each figure shows the fraction of respondents rating reasoning as more important (blue circles) and the fraction rating knowledge as more important (red crosshatches), separately by decile of the birth cohort of the respondent's first child (upper panel) or of the respondent (lower panel). Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence intervals (outer intervals, marked by line segments). Uniform confidence intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

A Proofs

Proof of Proposition 1

From Assumption 1 and equation (4) we have that

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

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

Because $\mathbf{P}_c>0$, an analogue of equation (4) holds for any pair of dimensions $(1,j)$. Thus given ρ the ratio K_{cj}/K_{c1} is identified for all c and j. 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 one, $\sum_j K_{cj}=J$. Then $\mathbf{K}_c$ is identified, because $\sum_j K_{cj}=\sum_j\left(K_{cj}/K_{c1}\right)K_{c1}=K_{c1}\sum_j\left(K_{cj}/K_{c1}\right)=J$.

Finally, $\overline{S}_c$ is identified for all c given ρ and $\mathbf{K}_c$ because

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

Proof of Corollary 1

Let $\hat{\mathbf{P}}_c=|\alpha\mathbf{P}_c|=|\alpha|\mathbf{P}_c$ for $\alpha\neq 0$. Because $\hat{P}_{c1}/\hat{P}_{cj}=P_{c1}/P_{cj}$ for all c and j, the arguments in the proof of Proposition 1 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

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

Proof of Proposition 2

From equation (1) we have that for each period t

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

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

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

where the last equality uses Assumption 2. It follows that

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

where $\tilde{B}_{t,t-c} = \left(B_{t,t-c} + \zeta_{t,t-c} - \tilde{\alpha}\mathbf{p}'_{t,t-c}\tilde{\mathbf{x}}_c\right)$ 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).

B Additional Tables and Figures

Appendix Table 1: Number of individuals by borth cohort, military enlistment and survey data

(a) *Military enlistment data*

Birth cohort	Number of individuals
1962	51,265
1963	54,520
1964	57,737
1965	54,276
1966	38,522
1967	47,198
1968	49,335
1969	48,308
1970	48,167
1971	50,496
1972	50,245
1973	46,912
1974	47,949
1975	44,874
Total	689,804

(b) *Survey data*

Birth cohort	Number of individuals
1948	5,040
1953	4,470
1967	3,818
1972	3,803
1977	1,902
Total	19,033

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.

Appendix Table 2: Summary of data and model implications

	Logical reasoning	Vocabulary knowledge
Initial lifetime skill premium, 1962	0.0048	0.0016
$P_{\underline{c}j}$	(0.0001)	(0.0001)
Change in lifetime skill premium, 1962–1975	-0.0007	-0.0007
$P_{\bar{c}j} - P_{\underline{c}j}$	(0.0001)	(0.0001)
Initial average skill rank, 1962	47.89	50.71
$\bar{x}_{\bar{c}j}$	(0.14)	(0.12)
Change in average skill rank 1962–1975	4.59	-2.72
$\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}$	(0.20)	(0.18)
Under estimated model:		
Change in average skill rank, 1962–1975 at initial skill premia	3.01	3.18
$\tilde{x}_{\bar{c}j}\left(\mathbf{P}_{\underline{c}}\right) - \tilde{x}_{\underline{c}j}\left(\mathbf{P}_{\underline{c}}\right)$	(0.20)	(0.22)
Share of observed change explained by change in skill premia	0.3455	2.1678
$1 - \frac{\tilde{x}_{\bar{c}j}\left(\mathbf{P}_{\underline{c}}\right) - \tilde{x}_{\underline{c}j}\left(\mathbf{P}_{\underline{c}}\right)}{\bar{x}_{\bar{c}j} - \bar{x}_{\underline{c}j}}$	(0.0180)	(0.1546)
Elasticity of substitution	0.3444	
$1/\left(\rho - 1\right)$	(0.1351)	

Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975. Section 4 describes estimation procedures. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates.

Appendix Table 3: Sensitivity of main results to different sample specifications

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 $\tilde{x}_{\bar{c}j}$		Change in average skill rank, 1962–1975 $\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}}$	
	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge	Logical reasoning	Vocabulary knowledge
(a) Baseline	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3455 (0.0180)	2.1678 (0.1546)
(b) Replace logical reasoning skill with logical-spatial composite	0.0043 (0.0001)	0.0021 (0.0001)	-0.0008 (0.0001)	-0.0006 (0.0001)	46.14 (0.13)	50.80 (0.12)	5.74 (0.20)	-2.78 (0.18)	0.4730 (0.0178)	2.2006 (0.1517)
(c) Age range 35–55	0.0049 (0.0001)	0.0019 (0.0001)	-0.0008 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.4153 (0.0202)	2.0432 (0.1459)
(d) Age range 30–60	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3554 (0.0183)	2.1502 (0.1532)
(e) Extrapolate for ages 35+	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0008 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3362 (0.0179)	2.1844 (0.1560)
(f) Extrapolate with last age	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3477 (0.0178)	2.1639 (0.1540)
(g) NPV with discount factor 0.9	0.0048 (0.0001)	0.0014 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.2869 (0.0167)	2.2723 (0.1622)
(h) NPV with discount factor 0.93	0.0048 (0.0001)	0.0015 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3173 (0.0173)	2.2181 (0.1582)
(i) NPV with discount factor 0.99	0.0048 (0.0001)	0.0017 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3702 (0.0186)	2.1236 (0.1513)
(j) Quadratic smoothing for estimated skill premium series	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3453 (0.0180)	2.1680 (0.1546)
(k) No smoothing for estimated skill premium series	0.0050 (0.0001)	0.0013 (0.0001)	-0.0009 (0.0002)	-0.0006 (0.0002)	47.89 (0.13)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.2861 (0.0364)	2.2737 (0.1767)

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 one bootstrap replicate from the calculation of standard errors for rows (b) and (k) due to values inconsistent with the model. Row (a) reproduces our baseline estimates from Appendix Table 2. Row (b) replaces the logical reasoning skill measure by 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 metal folding test where subjects are asked to identify a three-dimensional object that corresponds to an unfolded piece of metal (Carlstedt and Mårdberg 1993; Carlstedt 2000). Rows (c) and (d) vary the ages of working life that we consider for estimating the lifetime skill premia $\mathbf{P}_c$. Rows (e) and (f) change the ages over which we average the estimated premia $\mathbf{p}_{c+a,a}$ in order to infer premia for ages for which earnings data are unavailable. Rows (g)–(i) vary the discount factor δ that we use in the calculation of $\mathbf{P}_c$ in equation (3). Rows (j) and (k) use, respectively, a quadratic fit (second-order polynomial) and no smoothing at all, instead of a linear fit, to the relationship between estimated lifetime skill premia and cohort.

Appendix Table 4: Trends in lifetime skill premia using survey test scores as instruments

	Enlistment data	Enlistment + survey data	
	Linear trend	OLS	IV
Change from 1967 to 1972 in lifetime premium to:			
Logical reasoning skill (P_{c1})	-0.0003	0.0006	0.0021
	(0.00004)	(0.0007)	(0.0017)
Vocabulary knowledge skill (P_{c2})	-0.0003	-0.0003	-0.0015
	(0.00004)	(0.0007)	(0.0018)
Number of individuals (1967 cohort)	42,589	2,926	2,926
Number of individuals (1972 cohort)	45,722	3,454	3,454

Notes: This table 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 Figure 1. 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 4.1. 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. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates.

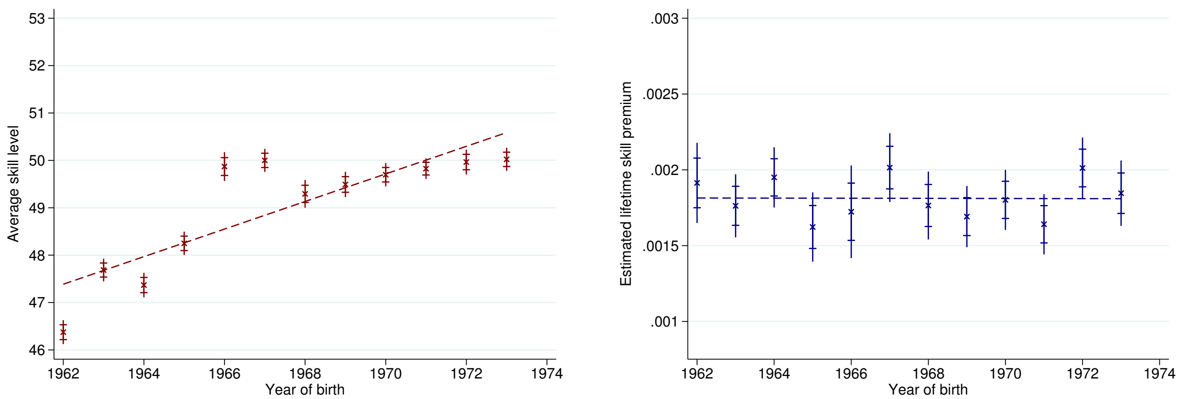
Appendix Table 5: Sensitivity of main results to adjusting for control variables

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 $\tilde{x}_{\bar{c}j}$		Change in average skill rank, 1962–1975 $\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}$		Share of observed change explained by change in skill premia $1 - \frac{\tilde{x}_{\bar{c}j}(\mathbf{P}_{\underline{c}}) - \tilde{x}_{\underline{c}j}(\mathbf{P}_{\underline{c}})}{\tilde{x}_{\bar{c}j} - \tilde{x}_{\underline{c}j}}$	
	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 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.89 (0.14)	50.71 (0.12)	4.59 (0.20)	-2.72 (0.18)	0.3455 (0.0180)	2.1678 (0.1546)
(b) Age at enlistment (indicators)	0.0047 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	49.05 (0.14)	51.99 (0.12)	3.94 (0.20)	-3.36 (0.18)	0.3981 (0.0235)	1.7468 (0.1014)
(c) Completed secondary education at age 18 (indicator)	0.0048 (0.0001)	0.0016 (0.0001)	-0.0007 (0.0001)	-0.0007 (0.0001)	47.10 (0.13)	49.87 (0.12)	4.24 (0.20)	-3.09 (0.18)	0.3685 (0.0204)	1.9173 (0.1183)
(d) ln(Height) and ln(Weight)	0.0047 (0.0001)	0.0015 (0.0001)	-0.0007 (0.0001)	-0.0006 (0.0001)	47.92 (0.13)	50.76 (0.13)	4.75 (0.20)	-2.66 (0.19)	0.3261 (0.0178)	2.2742 (0.1732)
(e) Non-cognitive skills (standardized within cohort)	0.0037 (0.0001)	0.0009 (0.0001)	-0.0009 (0.0001)	-0.0006 (0.0001)	48.64 (0.14)	51.46 (0.12)	4.46 (0.20)	-2.96 (0.18)	0.2498 (0.0227)	2.1966 (0.1450)

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 Appendix Table 2. Each subsequent row includes a different control variable or variables. Control variables are included when estimating cohort- and age-specific skill returns and are used to adjust the estimated average skill ranks, following Section 4.3. The measure of non-cognitive skills in specification (e) is standardized to have zero mean and unit standard deviation within each birth cohort.

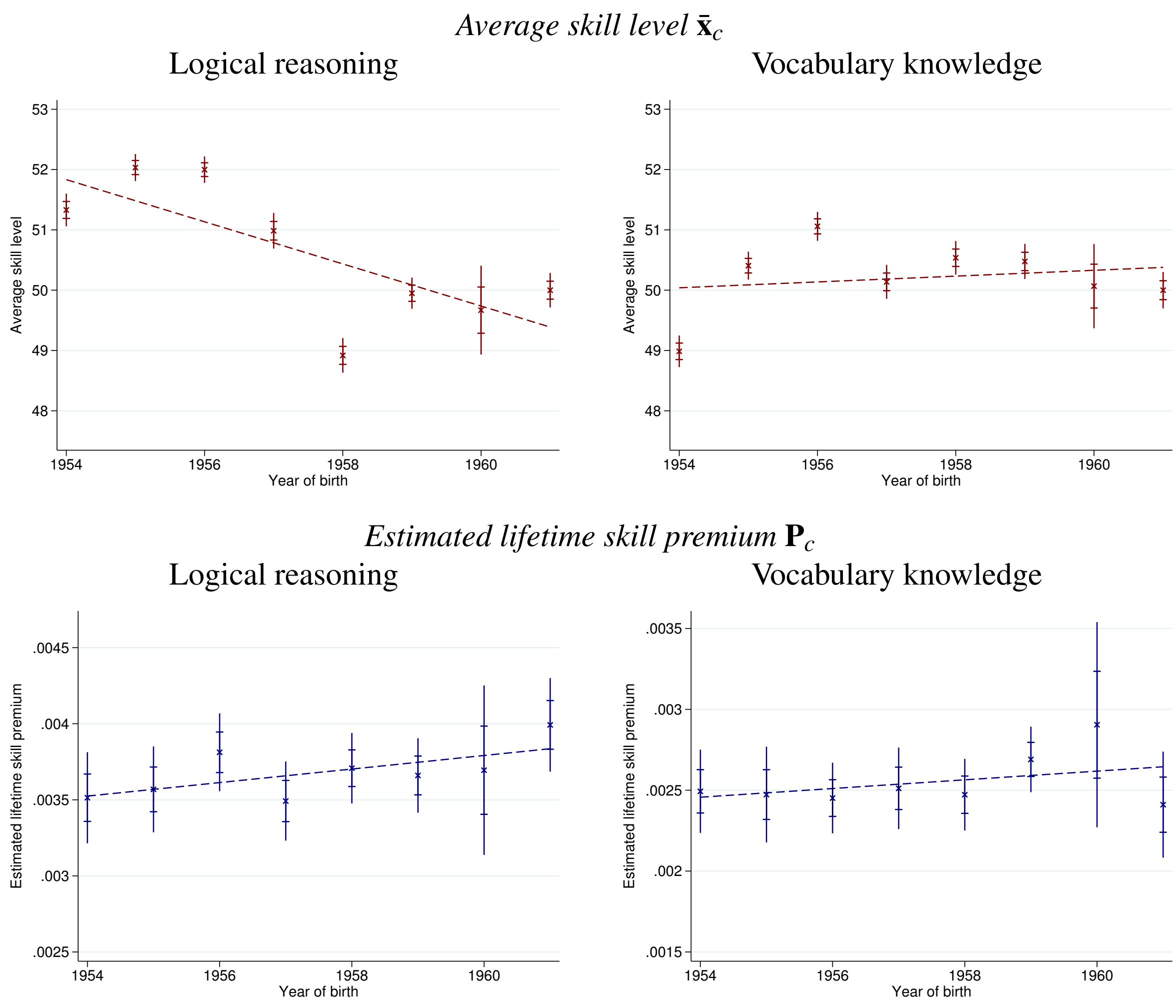
Appendix Figure 1: Trends in technical knowledge and technical knowledge premia across birth cohorts, military enlistment data

Average skill level $\bar{\mathbf{x}}_c$ *Estimated lifetime skill premium* $\mathbf{P}_c$



Notes: 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 the technical knowledge test for these cohorts. The left plot depicts the average technical knowledge 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 right plot depicts the estimated lifetime skill premium $\mathbf{P}_c$ for technical knowledge for each birth cohort, constructed as described in Section 4.1. 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 intervals (outer intervals, marked by line segments). Uniform confidence intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

Appendix Figure 2: Trends in skills and skill premia across birth cohorts 1954–1961, military enlistment data



Notes: Data are from the military enlistment sample covering birth cohorts 1954–1961. 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 4.1. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence intervals (outer intervals, marked by line segments). Uniform confidence intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

Appendix Figure 3: Structure of the survey of parents' perceptions

Panel A: Consent form

Stockholms universitet

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 >>

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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?

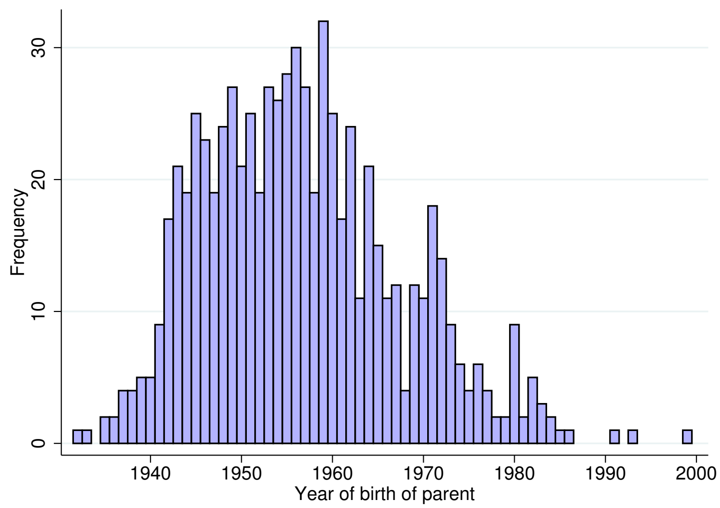
	Inte alls	Lite	Varken mycket eller lite	Mycket	Väldigt mycket
Att kunna tänka kritiskt och lösa problem logiskt.	○	○	○	○	○
Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord.	○	○	○	○	○

<< Föregående sida | Skicka nu

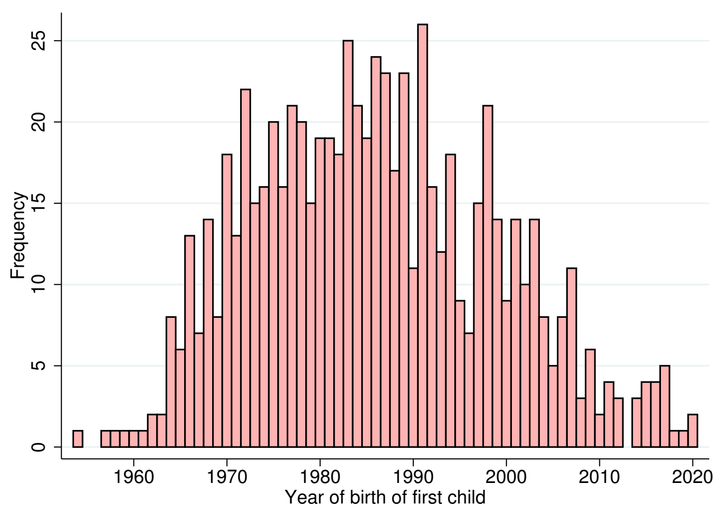
Notes: This figure shows the content and structure of the survey on parents' perceptions described in Section 3.2. Panel A displays the consent form and Panel B displays the survey form, both in the original Swedish.

Appendix Figure 4: Distributions of year of birth of respondent and first child in the survey of parents' perceptions

Panel A: Respondent

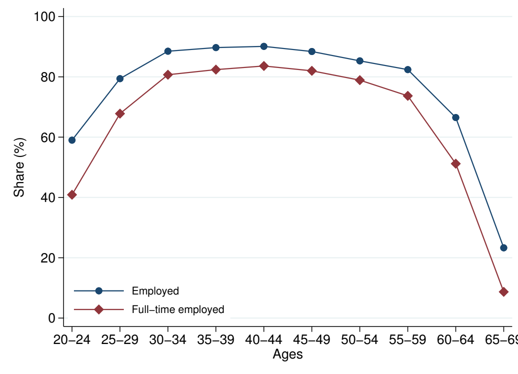


Panel B: Respondent's first child

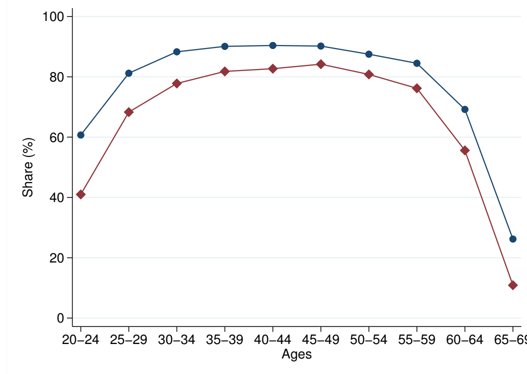


Notes: Data come from the survey of parents' perceptions described in Section 3.2. Panel A shows the distribution of the year of birth of the respondent. Panel B shows the distribution of the year of birth of the respondent's first child.

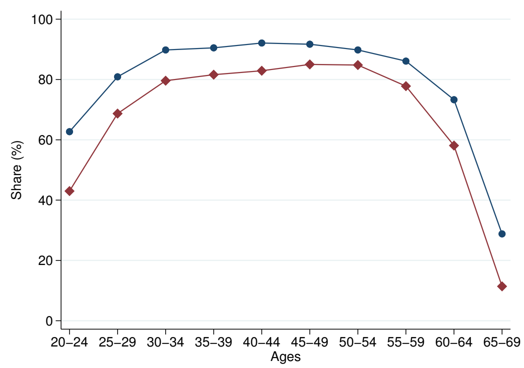
Appendix Figure 5: Male employment rates by age group for selected years



(a) 2010



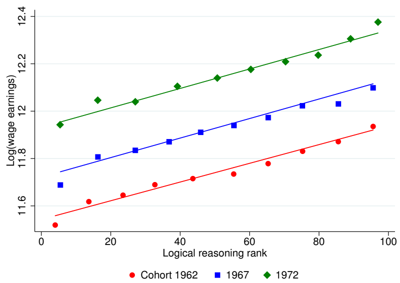
(b) 2015



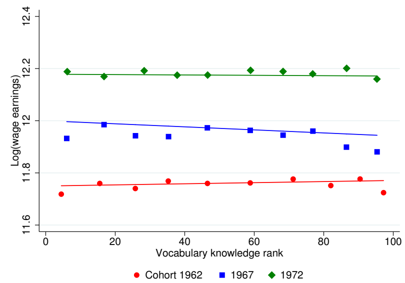
(c) 2019

Notes: 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 2020). 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.

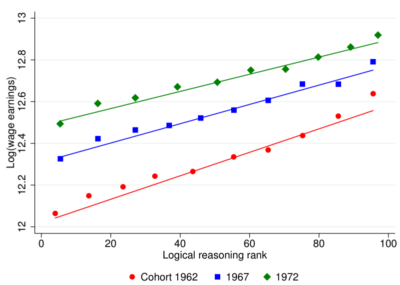
Appendix Figure 6: Illustrating the relationship between log(earnings) and skill percentile, military enlistment data



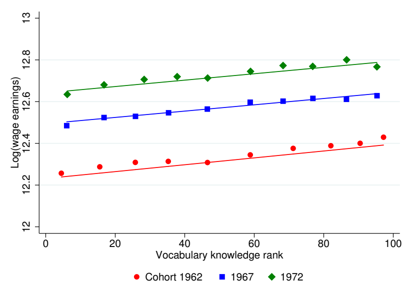
(a) Logical reasoning, age 30



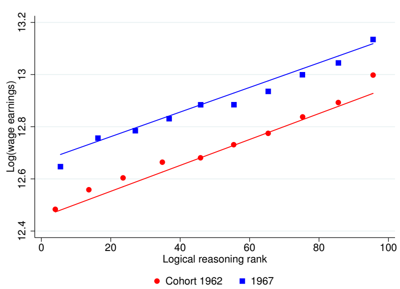
(b) Vocabulary knowledge, age 30



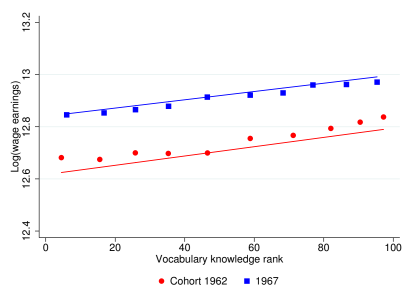
(c) Logical reasoning, age 40



(d) Vocabulary knowledge, age 40



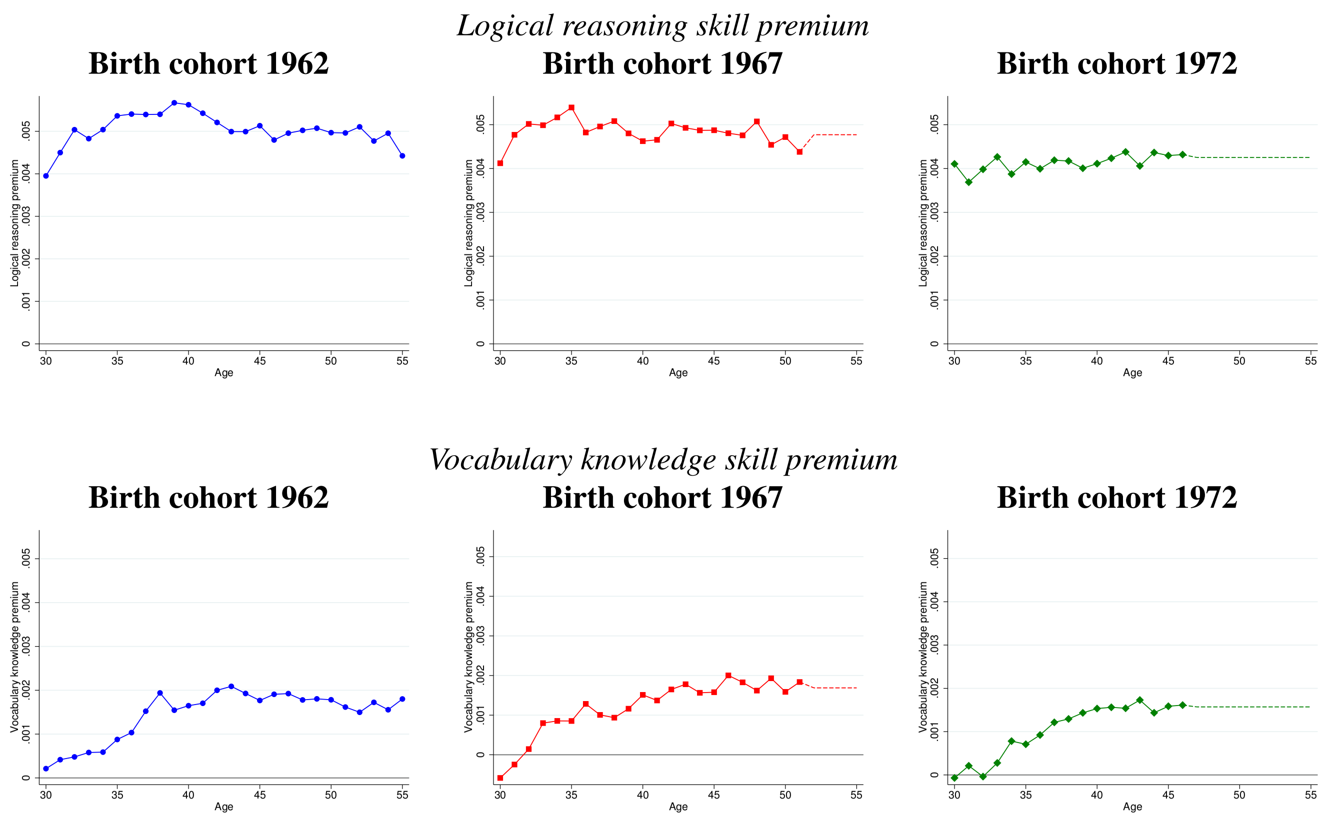
(e) Logical reasoning, age 50



(f) Vocabulary knowledge, age 50

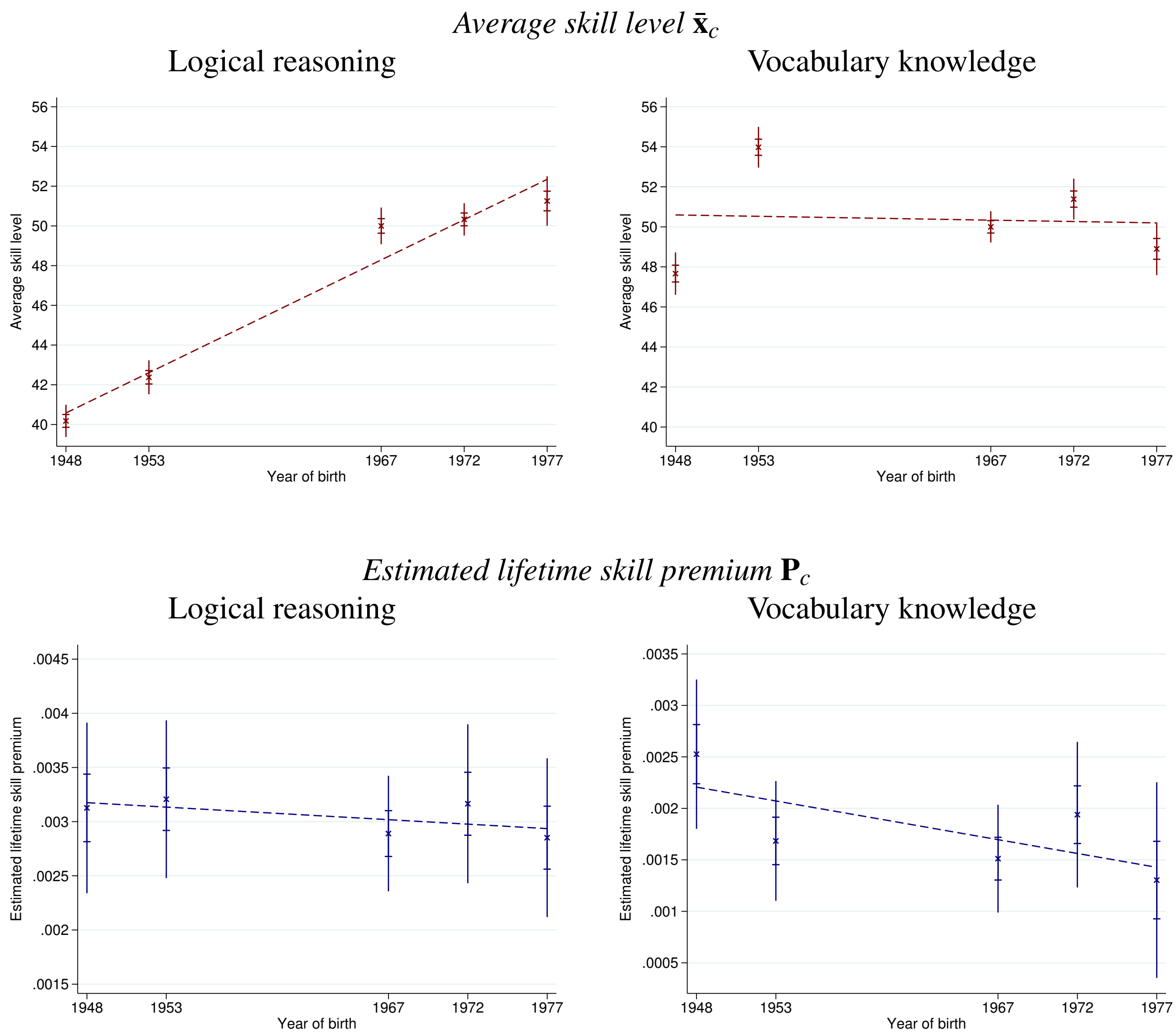
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. This figure illustrates the relationship between the mean of log annual earnings and logical reasoning and vocabulary knowledge skill for birth cohorts 1962, 1967 and 1972, 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 $\mathbf{p}_{c+a,a}$ of the given skill dimension, estimated from a regression of log(earnings) on logical and verbal skill, and whose intercept is chosen so that the line coincides with the decile coefficient at the fifth decile.

Appendix Figure 7: Illustrating the extrapolation of skill premia to ages with no earnings data, military enlistment data



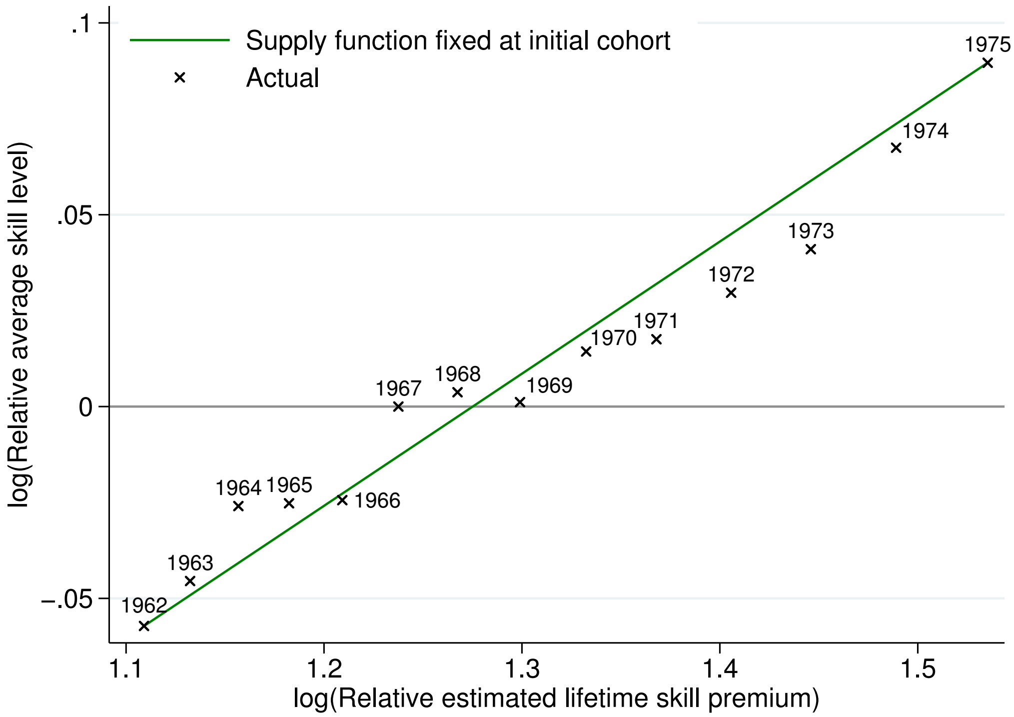
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plots illustrate how we estimate skill premia for ages in working life for which we do not observe earnings. The upper row of plots illustrate for logical reasoning and the lower row of plot illustrates for vocabulary knowledge, both 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 skill premium across all ages 40+ for which we do observe earnings (markers).

Appendix Figure 8: Trends in skills and skill premia across birth cohorts, survey data



Notes: Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972 and 1977. 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, constructed as described in Section 4.1. Each plot depicts both 95 percent pointwise confidence intervals (inner intervals, marked by dashes) and 95 percent uniform confidence intervals (outer intervals, marked by line segments). Uniform confidence intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019). Each plot depicts the line of best fit through the estimated points.

Appendix Figure 9: Illustration of relative supply function, military enlistment sample



Notes: This figure uses data from the military enlistment sample for men born between 1962 and 1975, with tests typically taken at age 18 or 19. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative estimated lifetime skill premia, $\ln(P_{c1}/P_{c2})$, based on the linearized skill premia depicted in Figure 1. The green line shows the relative skill supply function estimated for the 1962 birth cohort, i.e., the relationship between $\ln(P_{c1}/P_{c2})$ and $\ln\left(\tilde{x}_{\underline{c},1}(\mathbf{P}_c)/\tilde{x}_{\underline{c},2}(\mathbf{P}_c)\right)$.