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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 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 36 percent 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.

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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 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 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 by the tax agency 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 differ-

¹Rindermann 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).

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

³There 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).

⁴Deary (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).

ent 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 4.5 percentile points relative to the distribution in the 1967 cohort. The estimated lifetime earnings premium to an additional percentile point of logical reasoning performance 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 2.8 percentile points. The estimated lifetime premium to an additional percentile point of vocabulary knowledge 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 premium to vocabulary knowledge relative to logical reasoning fell by 40 log points. Seen through the lens of our model, the declining relative premium to crystallized intelligence drove a reallocation of effort towards 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 2.9 and 3.0 percentile points, respectively. The estimated model thus implies that trends in labor market returns explain 36 percent of the growth in logical reasoning performance ($36 \approx 100 \times \frac{4.5-2.9}{4.5}$) 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, though 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, secondary school completion, and a measure of non-cognitive skills, which we measure in administrative data. Although adjusting for covariates is conceptually delicate, as some covariates may themselves respond to labor market returns, 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. In a review of pedagogical scholarship, and an original quantitative text analysis, we find evidence of a trend towards increasing emphasis on reasoning relative to knowledge in primary school curricula in Sweden. Turning to the demand for skill, 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 paper, where we also discuss evidence on sensitivity to departures from key assumptions and to adjusting for covariates. 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 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 main analyses are limited to men only, though in an appendix we show results for women in the survey sample.

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 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

Much prior work in economics and other fields studies trends in the level of and returns to skills,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)

⁵Our 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; Doepke et al. 2019). In particular, unlike much of the work reviewed in, e.g., Heckman and Mosso (2014), we treat the skill investment decision as static and do not model the dynamics of skill formation during childhood.

⁶Dickens 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.

⁷For 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.

⁸For 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.

⁹These 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).

estimate trends in the returns to cognitive and non-cognitive skills in Sweden. None of these papers uses an estimated economic 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 main findings. Section 5 discusses additional evidence related to the mechanisms in the model. Section 6 concludes.

2 Model

2.1 Production and Earnings

There is a finite population of workers $i \in \mathcal{N}$, each of which is associated with a cohort $c(i) \in \{\underline{c}, \dots, \bar{c}\}$. Each worker is characterized by a skill level $\mathbf{x}_i \in \mathbb{R}_{\geq 0}^J$ 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 $a(i, t) \in \{1, \dots, A\}$ 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 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.

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

¹¹That 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

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

where $\nabla F_{t,a}$ is the gradient of $F_t(\mathbf{X}_t)$ at \mathbf{X}_t with respect to the 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. Motivated by a large-population setting, we will 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 $\mathbf{x}_{t,a(i,t)}$ of individuals who share worker i 's experience level at time t to get

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

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

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

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 .

¹²Specifically,

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

2.2 Skill Investment

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

$$\begin{aligned} \mathbf{x}_i &\geq \boldsymbol{\mu}_i \\ S_{c(i)}(\mathbf{x}_i - \boldsymbol{\mu}_i) &\leq \bar{S}_{c(i)} \end{aligned} \quad (2)$$

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

We can think of $\mathbf{x}_i - \boldsymbol{\mu}_i \in \mathbb{R}_{\geq 0}^J$ as the skill investment of individual i , i.e., the increment in skills over and above the individual's endowment $\boldsymbol{\mu}_i$. The endowment $\boldsymbol{\mu}_i$ represents cross-sectional differences within a cohort, say in ability or access to schooling. The budget \bar{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 \bar{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.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 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 lifecycle, $\{\mathbf{p}_{c(i)+a,a}\}_{a=1}^A$. 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 (2), where

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

is the net present value of the skill premia $\mathbf{p}_{c(i)+a,a}$ at different experience levels a , normalized by

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

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 (3) with its expectation.¹⁴ 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 $\mathbf{p}_{c(i)+a,a}$.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 $S_{c(i)}(\tilde{\mathbf{x}}_i) \leq \bar{S}_{c(i)}$, where $\tilde{\mathbf{x}}_i = \mathbf{x}_i - \mu_i$. The solutions to this problem depend only on the cohort $c(i)$ of the worker and not on the worker's identity. In this sense, within-cohort variation in skill levels arise 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 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 $S_c(\cdot)$ takes the constant elasticity form

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

where $\mathbf{K}_c \in \mathbb{R}_{>0}^J$ is a vector 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 substi-

¹⁴That is, taking $E_c[\cdot]$ 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

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

¹⁵Specifically, 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 $a \in \{1, \dots, A\}$, with $\Lambda_{c,a} > -I_J$ for all c, a . Then we have that $\mathbf{p}'_{c(i)+a,a} = \tilde{\mathbf{p}}'_{c(i)+a,a} \prod_{a'=1}^a (\Lambda_{c(i),a'} + I_J)$ where $\tilde{\mathbf{p}}_{c(i)+a,a}$ are the premia to the worker's skills $\mathbf{x}_{i,a}$ at experience level a .

¹⁶To see this, start with an endowment $\hat{\mu}_i$ with mean $\hat{\mu}_c = \frac{\sum_{\{i:c(i)=c\}} \hat{\mu}_i}{|\{i:c(i)=c\}|}$ in cohort c , where $\hat{\mu}_c$ need not be zero. The problem of maximizing $\mathbf{P}'_{c(i)} \hat{\mathbf{x}}_i$ subject to $\hat{\mathbf{x}}_i \geq \hat{\mu}_i$ and $S_{c(i)}(\hat{\mathbf{x}}_i - \hat{\mu}_i) \leq \bar{S}_{c(i)}$ is equivalent to the problem of maximizing $\mathbf{P}'_{c(i)} \mathbf{x}_i$ subject to (2) where $\mathbf{x}_i = \hat{\mathbf{x}}_i - \hat{\mu}_{c(i)}$ and $\mu_i = \hat{\mu}_i - \hat{\mu}_{c(i)}$. Here μ_i has mean zero within each cohort by construction.

tutability 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 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 $\{(\mathbf{P}_c, \tilde{\mathbf{x}}_c)\}_{c=\underline{c}}^{\bar{c}}$ 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

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

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, 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 $\frac{P_{\underline{c}1}}{P_{\underline{c}2}} \neq \frac{P_{\bar{c}1}}{P_{\bar{c}2}}$, 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

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

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

budget \bar{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.

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.*

Corollary 1 allows that the econometrician may 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 non-market 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 $\tilde{\mathbf{x}}_c = \bar{\mathbf{x}}_c$ for $\bar{\mathbf{x}}_c$ 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*

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

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,*

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

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

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. 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 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 relative skill levels 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

¹⁸Following 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 $\text{sgn}\left(\ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{c2}} / \frac{\tilde{x}_{c1}}{\tilde{x}_{c2}}\right)\right) = \text{sgn}\left(\ln\left(\frac{P_{c1}}{P_{c2}} / \frac{P_{c1}}{P_{c2}}\right)\right) \neq 0$, are compatible with our model and with Assumption 1.

¹⁹Cliffordson 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.

some (e.g., nutrition) have larger effects on fluid than crystallized intelligence.²⁰ 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).²¹

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.²²

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} .

3 Data

3.1 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 in 1980 or later (War Archives 2016). These tests are called Enlistment Battery 80. Carl-

²⁰In 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).

²¹Pietschnig and Voracek (2015, pp. 290-291) 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, p. 146). Simons et al. (2016) argue that there is limited evidence of effects of interventions such as video-game playing on broader cognitive performance.

²²Say that $\frac{P_{c1}}{P_{c2}} > \frac{P_{c1}}{P_{c2}}$. If $\frac{1}{c-c} \sum_{c=c}^{c-1} \left[\ln \left(\frac{K_{c+1,1}}{K_{c+1,2}} \right) - \ln \left(\frac{K_{c1}}{K_{c2}} \right) \right] > 0$, then our construction will understate the elasticity of substitution $\frac{1}{\rho-1}$. If $\frac{1}{c-c} \sum_{c=c}^{c-1} \left[\ln \left(\frac{K_{c+1,1}}{K_{c+1,2}} \right) - \ln \left(\frac{K_{c1}}{K_{c2}} \right) \right] < 0$, then our construction will overstate it.

stedt (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 and earlier testing ages, 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 1977.²³ Härnqvist (1998) and Svensson (2011) describe the survey and tests in more detail. We focus on males to parallel the military enlistment sample. Appendix Figure 1 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 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 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.

We include in our analysis only those individuals for whom we observe valid logical reasoning and vocabulary knowledge scores. 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 1967.²⁴ 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 3 shows how our results change when we instead measure an individual's skill by expressing the individual's score on each test as a percent of the maximum possible score. Appendix Table 1 shows the number of individuals in each birth cohort for each data source.

Both data sources also include a test of spatial reasoning. Appendix Table 3 shows how our re-

²³We exclude the 1982 birth cohort because available data on earnings are more limited for this cohort.

²⁴Specifically, 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.

sults change when we combine logical and spatial reasoning skills into a single composite measure of fluid intelligence. For completeness, Appendix Figure 2 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. Appendix Figure 3 shows trends in the level 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).

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 1968–2018.²⁵ For each individual i in each year t , we let w_{it} be the total gross labor market earnings. Appendix Table 3 shows how our results change when we additionally include business income, which we obtain for 1990–2018 from Statistics Sweden (2021).²⁶

Portions of our analysis use data on additional covariates. From the enlistment data (War Archives 2016), we obtain the date on which an individual took the enlistment tests, as well as the individual’s height and weight as of enlistment. From other sources we obtain administrative data on each individual’s employment history (Statistics Sweden 2020a), foreign-born status (Statistics Sweden 2014a), and secondary schooling completion (Statistics Sweden 2014c).

3.2 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.

²⁵Data 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, p. 137-138). Data for 1968–1989 are from Statistics Sweden (2014b), where we approximate the concept described in Statistics Sweden (2016a, p. 137-138) using the available data fields.

²⁶We define the resulting total income measure using the concept described in Statistics Sweden (2016a, pp. 141-142).

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.

Appendix Figure 4 gives screenshots of the consent form and survey form. Appendix Figure 5 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 6 shows that full-time work tends to be highest during these years. Appendix Table 3 shows how our findings change when we alter the beginning or ending year of working life, and when we restrict to workers who are employed year-round in a typical year.

We estimate the parameter $\mathbf{p}_{t,a}$ in equation (1) by ordinary least squares 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 $c + a \leq T$, for T the most recent year of earnings data available. Appendix Figure 7 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 8 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 $c \in \{\underline{c}, \dots, \bar{c}\}$. 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{x}_c and the estimated lifetime skill premia \mathbf{P}_c across cohorts in the enlistment data along with their 95 percent pointwise and 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 plotted series.

The top row of plots in Figure 1 shows that logical reasoning skill rose, on average, by 4.5 percentile points, relative to the 1967 distribution, across the birth cohorts from 1962 to 1975. By contrast, vocabulary knowledge skill fell, on average, by 2.8 percentile points. Appendix Figure 9 depicts the cumulative distribution functions of skills in the 1962 and 1975 cohorts.

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 percentile point of logical reasoning skill fell from 0.48 to 0.41 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 knowledge.²⁷ Appendix Figure 10 depicts estimated lifetime skill premia based on a generalization of equation (1) that allows interactions between the skill dimensions.

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 (5). Figure 3 shows that a similar qualitative pattern obtains in our survey sample, which is smaller and for which estimates tend to be less precise. Appendix Figure 11 depicts the underlying estimates of skill levels and lifetime skill premia in the survey sample.

Under the conditions in 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 Appendix B, 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

²⁷Prior 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.

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.

4.2 Model Estimates and Counterfactuals

We estimate the skill supply function $\tilde{x}_c(\cdot)$ 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{x}_c in each cohort as our estimate of \tilde{x}_c . We take the linear fit in Figure 1 as our estimate of the lifetime skill premia \mathbf{P}_c .²⁸ 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 2 reports estimates of key parameters. Appendix Table 3 shows how our findings change when we use a quadratic fit and when we do not smooth premia at all.

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}_{c_1} . In the counterfactual scenario, logical reasoning skill increases by 2.9 percentile points instead of 4.5 as in the actual data. Vocabulary knowledge skill increases by 3.0 percentile points rather than falling by 2.8 percentile points. In this sense, according to the model, changes in the lifetime skill premia \mathbf{P}_c account for 36.1 percent of the increase in logical reasoning skill (with a standard error of 1.5 percent), and for more than the entire decline in vocabulary knowledge skill.

To unpack the findings in Figure 4, begin with estimation of the elasticity of substitution $\frac{1}{\rho-1}$. Under Assumption 1, all 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 net change in relative skill levels to the net change in relative skill premia. Appendix Figure 12 illustrates by plotting the log of the relative estimated average skill level $\ln(\bar{x}_{c1}/\bar{x}_{c2})$ against the log of the relative average skill premia $\ln(P_{c1}/P_{c2})$, estimated based on the linear fit in Figure 1.

²⁸Consistent with the regularity condition in Proposition 1, based on the linear fit we reject the null hypothesis that $\ln(P_{c1}/P_{c2}) = \ln(P_{c1}/P_{c2})$ at conventional significance levels ($p = 0.0004$).

Under Assumption 1, the linear relative supply curve $\ln(\tilde{x}_{c1}(\cdot)/\tilde{x}_{c2}(\cdot))$ defined by the estimated skill supply function $\tilde{x}_c(\cdot)$ 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 $\frac{1}{\rho-1} = 0.365$, which is in turn the slope of the line $\ln(\tilde{x}_{c1}(\cdot)/\tilde{x}_{c2}(\cdot))$ depicted on the plot.

Next, consider estimation of the remaining parameters of the skill supply function $\tilde{x}_c(\cdot)$. Given the data, under any elasticity of substitution less than about 0.95, 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, i.e., 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, implying 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 supply function in equation (5), our discussion has focused on ratios of skill premia rather than on their differences. An alternative model that focuses instead on differences in premia might reach a different conclusion regarding the role of changes in premia in explaining cohort trends in skill levels. To illustrate why, Appendix Figure 13 presents an analogue of the scatterplot in Appendix Figure 12, but replacing log ratios of skill levels and skill premia with their differences. Appendix Figure 13 shows that the difference in premia between logical reasoning and vocabulary knowledge did not rise across successive cohorts in the way that Appendix Figure 12 shows that the ratio of premia did. Following Figure 1, 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).

4.3 Sensitivity to Assumption 1

Figure 5 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 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 4 and Appendix Table 2.

A reader can use Figure 5 to gauge the effect of a given departure from Assumption 1 on our conclusions. Figure 5 thus improves transparency in the sense of Andrews et al. (2017, 2020) and Andrews and Shapiro (forthcoming).

To illustrate the utility of Figure 5 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 does not affect performance on the logical reasoning test. We estimate that, relative to the 1962 birth cohort, members of the 1975 birth cohort spent 0.45 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 5 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 5 to calculate that changes in lifetime skill premia explain 54.7 percent of the observed increase in logical reasoning skill, which is 18.6 percentage points more than our baseline estimate of 36.1 obtained under Assumption 1.²⁹ Figure 5 enables similar calculations for any quantifiable shock to the relative supply of skills.

²⁹Carlsson 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 0.45 more years of schooling at enlistment than those born in 1962. As there are roughly 180 schooling days per year in Sweden (Carlsson et al. 2015, p. 538), this implies an increase of 0.0916 standard deviations in vocabulary knowledge skill. Interpolating around the median test score, we estimate that an increase of 0.0916 standard deviations in vocabulary test score is equivalent to an increase of 3.76 percentile points among those born in 1962. Based on the skill levels reported for the 1962 cohort in Appendix Table 2, an increase of 3.76 percentile points in vocabulary knowledge skill would have reduced the log ratio of logical reasoning and vocabulary knowledge skills by 0.071, or by 0.485 of the observed change. Given a relative supply shock of -0.485, Figure 5 implies that changes in skill premia account for 54.7 percent of the observed increase in logical reasoning.

4.4 Sensitivity to Controls

We explore the sensitivity of our conclusions to adjusting for covariates. We adjust both the estimated trend in mean skills \bar{x}_c 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.³⁰ 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 \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 the time of enlistment or at age 18, $\log(\text{height})$ and $\log(\text{weight})$ measured at the time of enlistment, a measure of non-cognitive skills taken 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 27 percent of the increase in logical skill, and for more than the entire decline in vocabulary knowledge skill.

³⁰Within the model in Section 2, we may think of this exercise as re-normalizing the skill endowment μ_i to have cohort-specific mean $\Gamma\bar{\mathbf{d}}_c$ where $\bar{\mathbf{d}}_c$ 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 .

5 Trends in Emphasis among Parents, Schools, and Occupations

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. In Sections 5.1 and 5.2, 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.

Implicitly, our model attributes changes in skill premia to changes in the production technology F_t . In Section 5.3, we explore whether changes in the occupation mix favor reasoning-intensive as opposed to knowledge-intensive occupations, consistent with the trends in relative premia that we observe.

5.1 Parents

Panel A of Figure 6 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. 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.

5.2 Schools

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 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,³¹ 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 Curricu-

³¹For 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, p. 13). The 1980 Curriculum repeats this language, quoting it as part of the Education Act (Skolöverstyrelsen 1980, p. 13).

lum.³²

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. 205). Similar trends have been observed in other areas of study.³³ These trends seem consistent with a greater emphasis on reasoning as compared to knowledge,³⁴ 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 6).

Appendix Figure 14 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 vs. knowledge during the cohort’s primary school years. The figure shows a trend across cohorts toward greater emphasis on reasoning relative to knowledge. Appendix Figure 15 lists the set of keywords we use and provides more details on data construction.

5.3 Occupations

Appendix Figure 16 shows trends across cohorts in the reasoning vs. knowledge intensity of occupations, measured as the percentile rank in the distribution of occupations for the 1967 cohort, and weighting occupations either by total employment or by total earnings among the men in our sample. We measure the relative reasoning vs. knowledge intensity of occupations in Sweden by matching occupations to those in the US and taking data on the importance of different abilities and knowledge from the O*NET 25.0 database (U.S. Department of Labor, Employment

³²For 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).

³³Löfdahl (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, pp. 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.

³⁴Larsson (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). Bietenbeck (2014) finds using test score data from the US that modern teaching practices promote reasoning skills whereas traditional teaching practices promote factual knowledge.

and Training Administration 2020). The plot shows evidence of a trend towards relatively more reasoning-intensive occupations. The trend is especially pronounced when weighting occupations by earnings. It is important to 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 US occupation codes is imperfect, and that the O*NET scores are static, and so do not reflect changes over time in the demands of different occupations. Still, we find the pattern in Appendix Figure 16 interesting in light of the growth in the relative premium to fluid intelligence that we document in Section 4.

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

Although we focus on two major dimensions of cognitive skill, in principle our model allows for multiple skill dimensions. Among other topics, it might be interesting to study whether the rising labor market return to non-cognitive skill (e.g., Deming 2017; Edin et al. forthcoming), has led to greater investments in non-cognitive skill. Such an analysis might, for example, replace equation (4) with a two-level constant elasticity transformation function along the lines of Sato (1967) or Goldin and Katz (2008, chapter 8, equations 1 and 2), with an “upper” level distinguishing non-cognitive and cognitive skills, and a “lower” level distinguishing different dimensions of each type of skill. Such an analysis would ideally use data on non-cognitive skills that can be compared across cohorts. The data we have available on non-cognitive skills is standardized by exam year and so does not have this property. We think using a different data source for such an analysis could be an interesting direction for future work.

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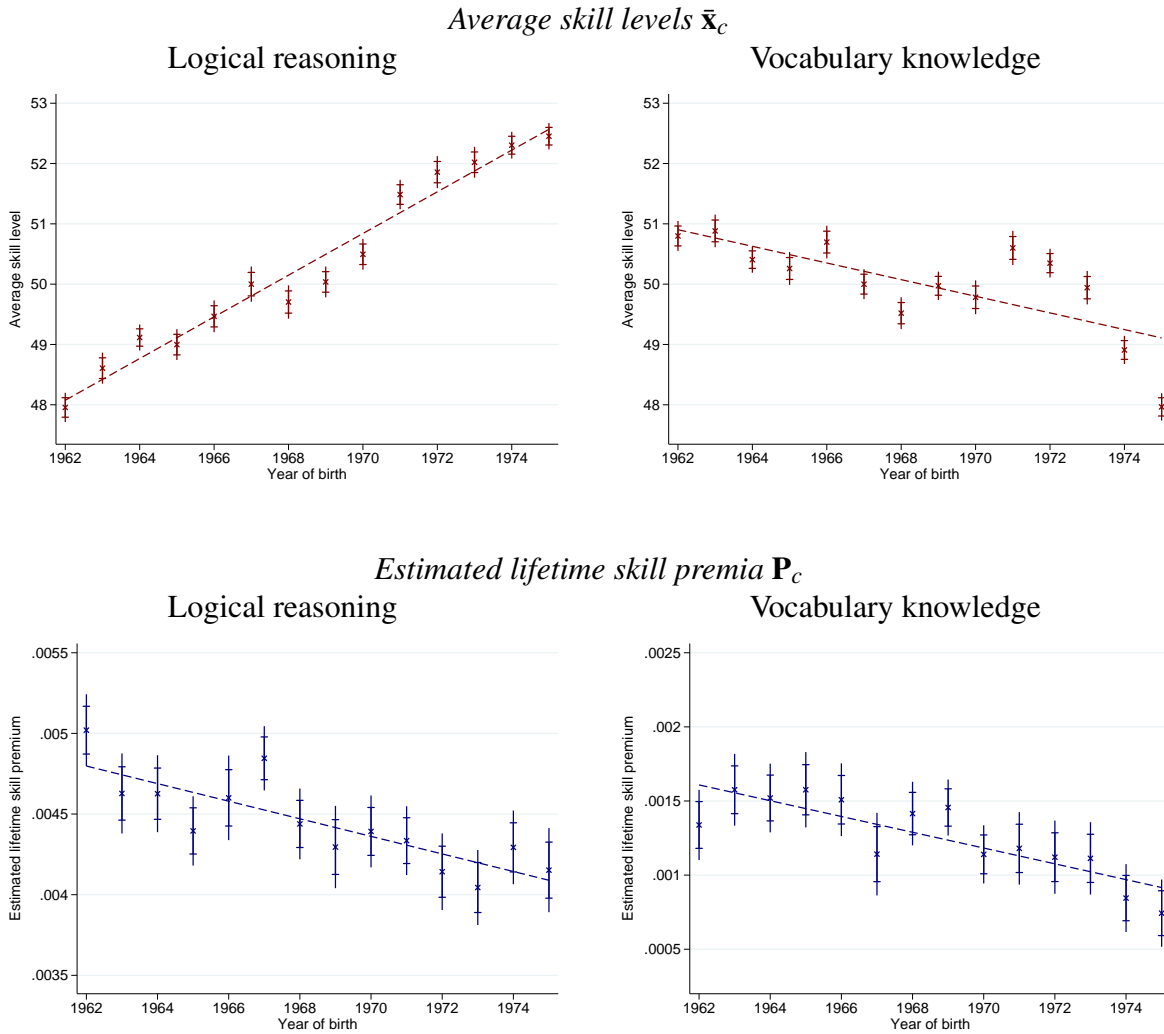
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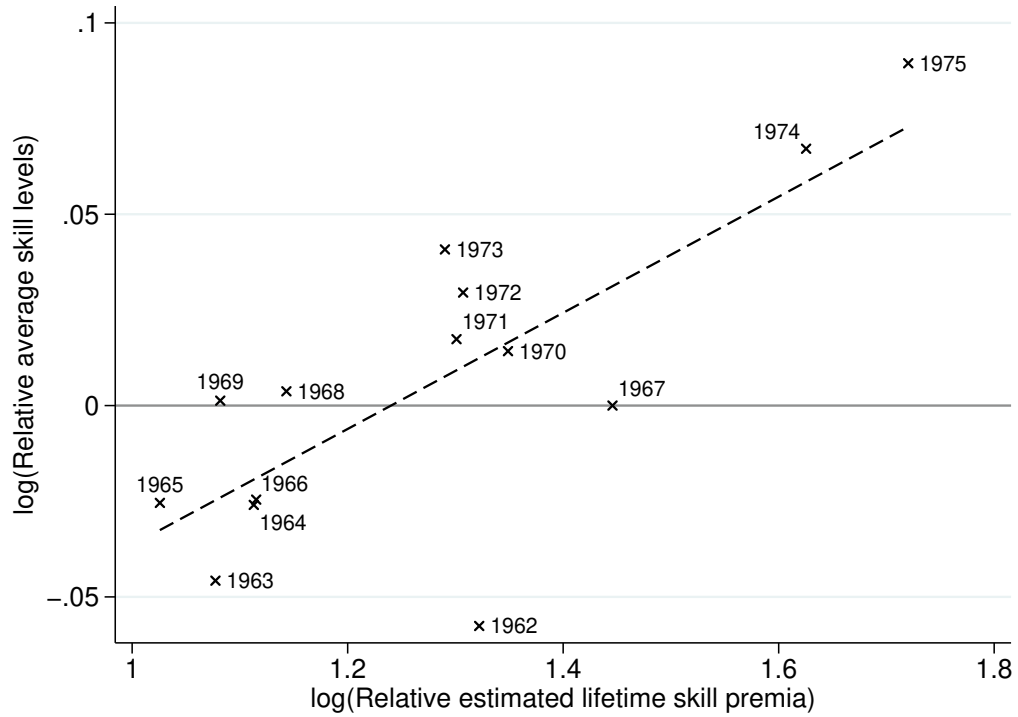
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Figure 1: Trends in skills and skill premia across birth cohorts 1962–1975, military enlistment data



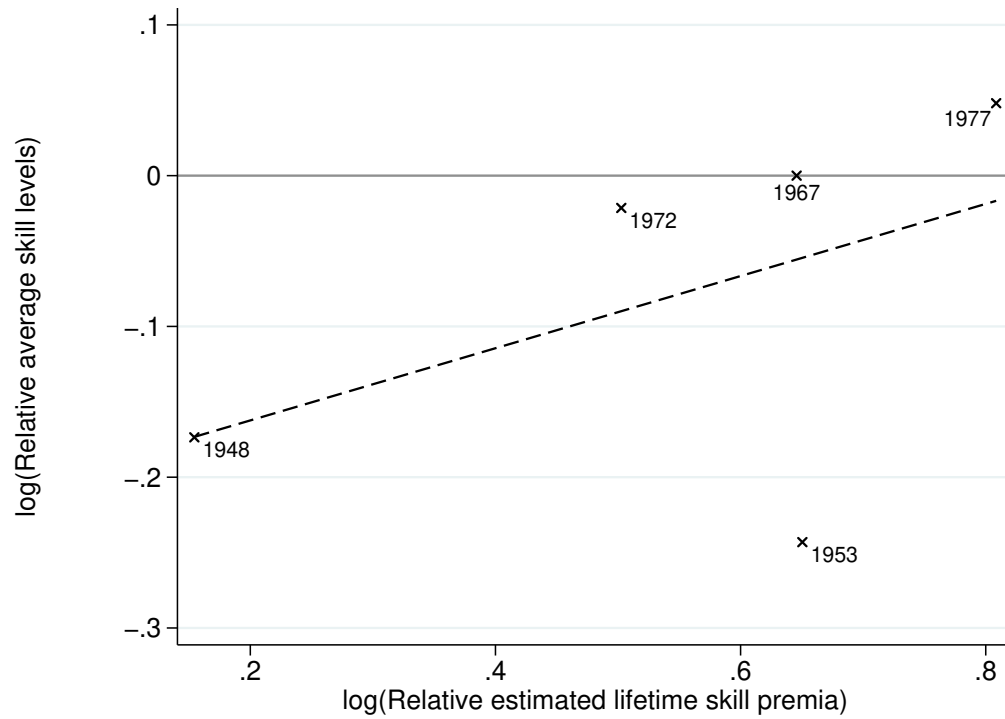
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The first row of plots depicts the average skill \bar{x}_c for each birth cohort c . Skills are expressed as a percentile of the distribution for the 1967 birth cohort. The 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



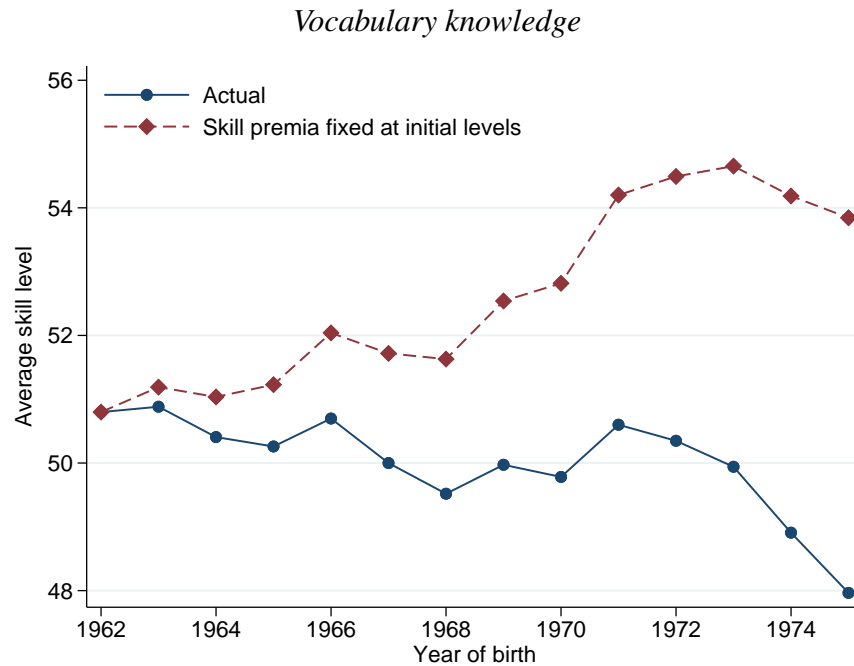
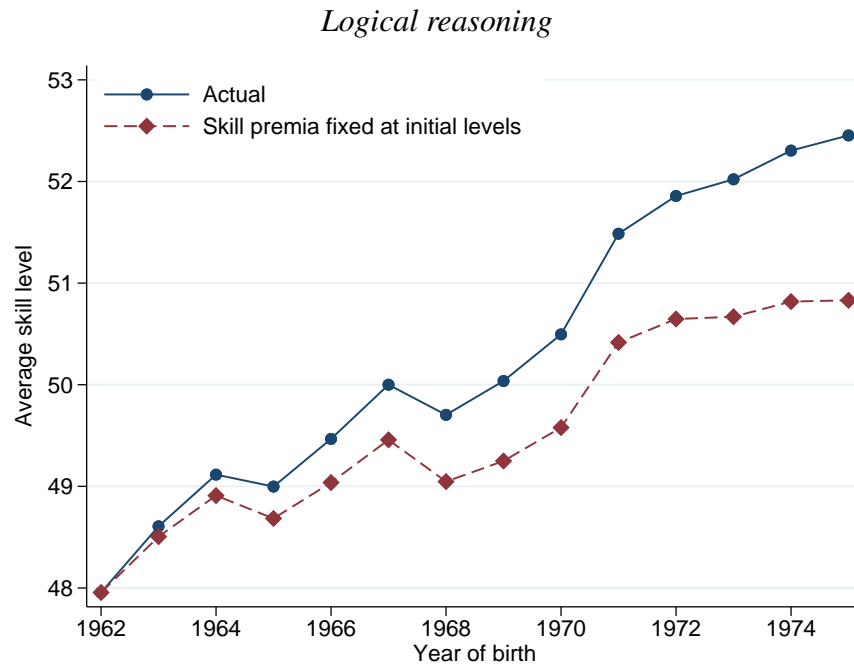
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative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



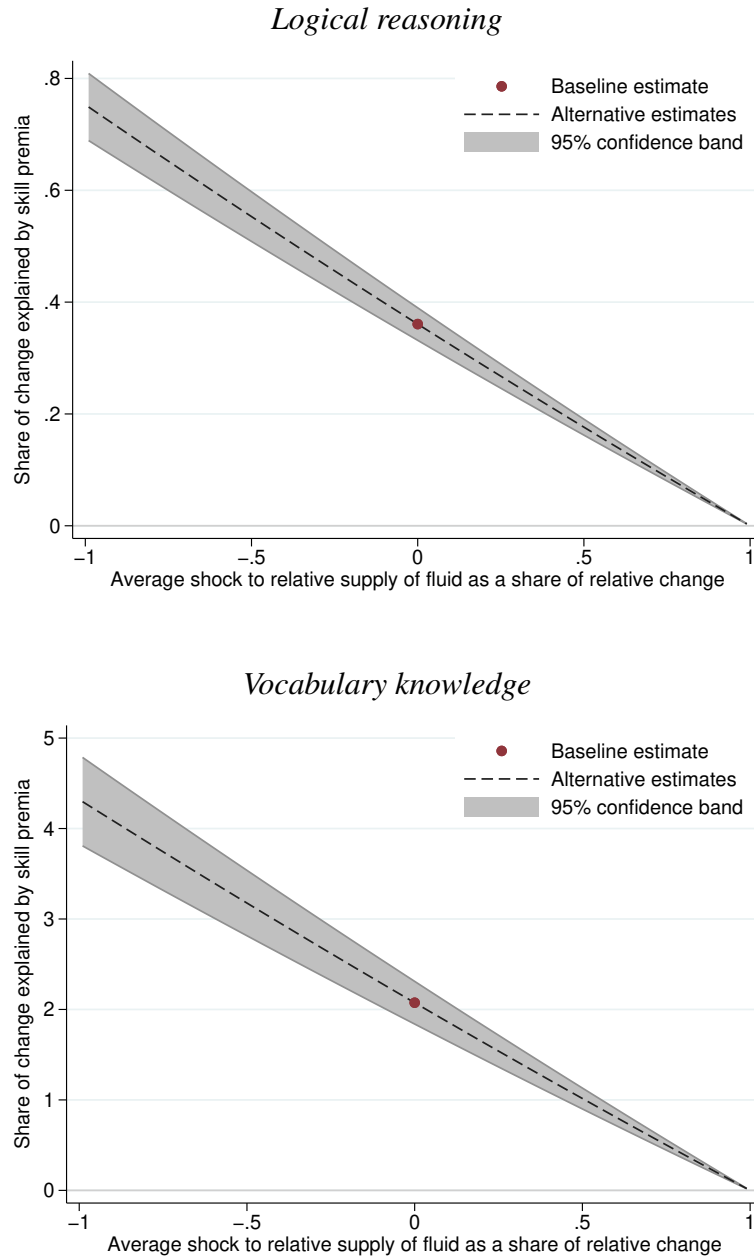
Notes: Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, and 1977, with tests typically taken at age 13. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative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



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{x}_c for each birth cohort c (“Actual”) and the predicted average skill $\tilde{x}_c(\mathbf{P}_c)$ 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.

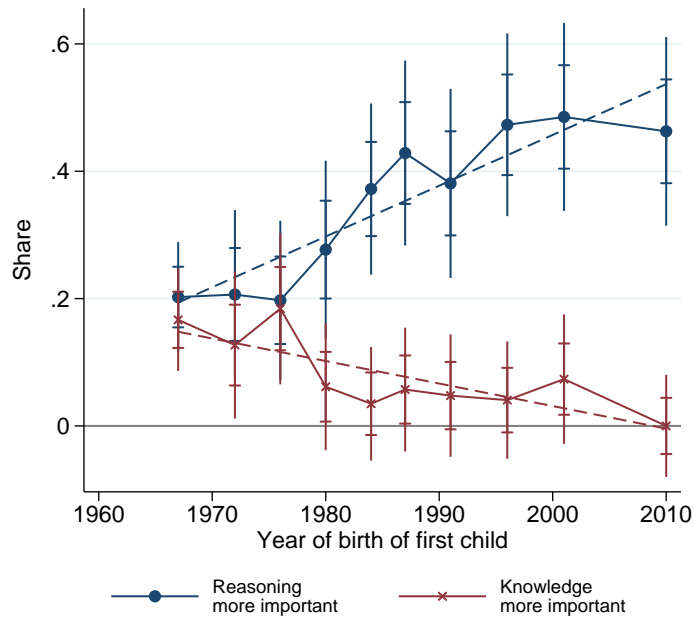
Figure 5: Sensitivity to departures from zero average relative supply shock



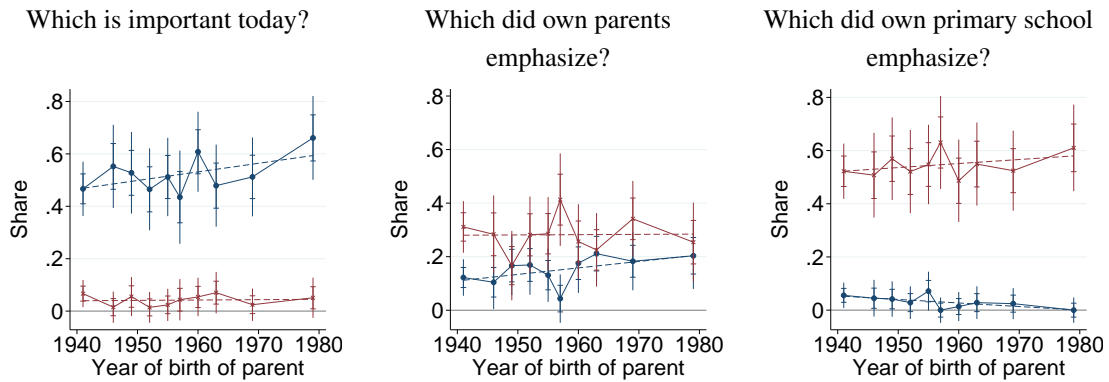
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. In each plot, the curve labeled “Alternative estimates” depicts the estimated share $1 - \frac{\bar{x}_{\bar{e}j}(\mathbf{P}_{\bar{c}}) - \bar{x}_{\bar{c}j}(\mathbf{P}_{\bar{c}})}{\bar{x}_{\bar{e}j} - \bar{x}_{\bar{c}j}}$ 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 $\ln \left(\frac{\bar{x}_{\bar{c}1}}{\bar{x}_{\bar{c}2}} \right) - \ln \left(\frac{\bar{x}_{\underline{c}1}}{\bar{x}_{\underline{c}2}} \right)$ 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 2, obtained under Assumption 1.

Figure 6: 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



Notes: Data are 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 (Panel A) or of the respondent (Panel B). 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 (5) we have that

$$\frac{1}{\rho - 1} = \frac{\ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{c2}}\right) - \ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{c2}}\right)}{\ln\left(\frac{P_{c1}}{P_{c2}}\right) - \ln\left(\frac{P_{c1}}{P_{c2}}\right)} \quad (6)$$

where the existence of the ratio on the right is guaranteed because $\frac{P_{c1}}{P_{c2}} \neq \frac{P_{c1}}{P_{c2}}$. 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 K_{cj}/K_{c1} is identified for all c and j via the relation

$$\ln\left(\frac{K_{cj}}{K_{c1}}\right) = \ln\left(\frac{\tilde{x}_{c1}}{\tilde{x}_{cj}}\right) - \frac{1}{\rho - 1} \ln\left(\frac{P_{c1}}{P_{cj}}\right). \quad (7)$$

From the budget constraint in (2) and the transformation function in (4), observe that multiplying \mathbf{K}_c by any positive constant κ is equivalent to multiplying \bar{S}_c by $\kappa^{\frac{1-\rho}{\rho}}$. Therefore fix the scale of \mathbf{K}_c by supposing that its average element equals one, i.e., $\sum_{j=1}^J K_{cj} = J$. Then $\sum_{j=1}^J K_{cj} = \sum_{j=1}^J (K_{cj}/K_{c1}) K_{c1} = K_{c1} \sum_{j=1}^J (K_{cj}/K_{c1}) = J$, which from (7) implies

$$K_{c1} = \frac{J}{\sum_{j=1}^J \frac{\tilde{x}_{c1}}{\tilde{x}_{cj}} \left(\frac{P_{cj}}{P_{c1}}\right)^{\frac{1}{\rho-1}}}. \quad (8)$$

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

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

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

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 directly establish identification of ρ and identification of \mathbf{K}_c up to a

normalization. Then \bar{S}_c is identified for all c given ρ and \mathbf{K}_c because

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

Proof of Proposition 2

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

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

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

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

where the last equality uses Assumption 2. It follows that

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

where $\tilde{B}_{t,t-c} = \left(B_{t,t-c} + \zeta_{t,t-c} - \tilde{\boldsymbol{\alpha}} \mathbf{p}'_{t,t-c} \tilde{\mathbf{x}}_c \right)$ and $\alpha = 1 + \tilde{\boldsymbol{\alpha}}$. Since $\tilde{\boldsymbol{\alpha}} \neq -1$, 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 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} .

Assumption 3. *The measurement error in each cohort c obeys*

$$\mathbb{E}(\hat{\mathbf{x}}_i - \mathbf{x}_i | \mu_i = \mu, c(i) = c) = 0 \quad (10)$$

and

$$\text{Var}(\hat{\mathbf{x}}_i - \mathbf{x}_i | c(i) = c) = \hat{\alpha} \text{Var}(\hat{\mathbf{x}}_i), \quad (11)$$

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

Assumption 3 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.

Assumption 4. *The values of z_{it} in each period t obey*

$$\mathbb{E}(\ln(z_{it}) | \hat{\mathbf{x}}_i - \mathbf{x}_i = \xi, \mu_i = \mu, c(i) = c) = \mathbb{E}(\ln(z_{it}) | \mu_i = \mu, c(i) = c) = \zeta_{t,t-c} + \tilde{\alpha} \mathbf{p}'_{t,t-c} \mu, \quad (12)$$

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

Assumption 4 implies that a version of Assumption 2 holds, and that unobserved determinants of log earnings are mean-independent of the measurement error in skills.

Assumptions 3 and 4 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.

Proposition 3. *Under Assumptions 3 and 4, 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,*

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

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

Proof of Proposition 3

Fix a cohort c and period t . From (10) and (11) we have that

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

From (1), (10), and (12) we have that

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

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

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

for $\alpha = (1 - \hat{\alpha})(1 + \tilde{\alpha}) > 0$. 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).

C Additional Tables and Figures

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

| <i>(a) Military enlistment data</i> | | <i>(b) Survey data</i> | |
|-------------------------------------|-----------------------|------------------------|-----------------------|
| Birth cohort | Number of individuals | Birth cohort | Number of individuals |
| 1962 | 51,504 | 1948 | 5,259 |
| 1963 | 54,671 | 1953 | 4,584 |
| 1964 | 57,705 | 1967 | 3,820 |
| 1965 | 54,218 | 1972 | 3,811 |
| 1966 | 38,456 | 1977 | 1,905 |
| 1967 | 47,076 | Total | 19,379 |
| 1968 | 49,226 | | |
| 1969 | 48,162 | | |
| 1970 | 48,038 | | |
| 1971 | 50,343 | | |
| 1972 | 50,033 | | |
| 1973 | 46,739 | | |
| 1974 | 47,814 | | |
| 1975 | 44,701 | | |
| Total | 688,686 | | |

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_{cj} | (0.0001) | (0.0001) |
| Change in lifetime skill premium, 1962–1975 | -0.0007 | -0.0007 |
| $P_{cj} - P_{cj}$ | (0.0001) | (0.0001) |
| Initial average skill rank, 1962 | 47.96 | 50.80 |
| \bar{x}_{cj} | (0.12) | (0.13) |
| Change in average skill rank 1962–1975 | 4.50 | -2.83 |
| $\bar{x}_{cj} - \bar{x}_{cj}$ | (0.17) | (0.18) |
| Under estimated model: | | |
| Change in average skill rank, 1962–1975 at initial skill premia | 2.87 | 3.05 |
| $\tilde{x}_{cj}(\mathbf{P}_c) - \tilde{x}_{cj}(\mathbf{P}_c)$ | (0.16) | (0.17) |
| Share of observed change explained by change in skill premia | 0.3607 | 2.0746 |
| $1 - \frac{\tilde{x}_{cj}(\mathbf{P}_c) - \tilde{x}_{cj}(\mathbf{P}_c)}{\bar{x}_{cj} - \bar{x}_{cj}}$ | (0.0148) | (0.1204) |
| Substitution parameter | | 3.74 |
| ρ | | (0.78) |
| [Implied elasticity of substitution $1/(\rho - 1)$] | | [0.3650] |

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. Estimates of \bar{x}_c and \mathbf{P}_c follow Figure 1 with the linear fit used as our estimate of \mathbf{P}_c . Estimates of $\tilde{x}_c(\cdot)$ follow the proof of Proposition 1. The unknown parameters are ρ and $\{\mathbf{K}_c, \bar{S}_c\}_{c=1}^C$. Take \bar{x}_c as our estimate of \tilde{x}_c . Then estimate the elasticity of substitution $\frac{1}{\rho-1}$ following equation (6). Next, estimate the relative cost parameters K_{c2}/K_{c1} in each cohort c following equation (7). From the normalization used in the proof of Proposition 1, estimate K_{c1} following equation (8), from which estimate K_{c2} using the ratio K_{c2}/K_{c1} . Finally, estimate the skill budget \bar{S}_c following equation (9).

Appendix Table 3: Sensitivity of main results to different specifications

| Specification | Initial lifetime skill premium, 1962 $P_{c,j}$ | | Change in lifetime skill premium, 1962–1975 $P_{c,j} - P_{c,j}$ | | Initial average skill level, 1962 $\bar{x}_{c,j}$ | | Change in average skill level, 1962–1975 $\bar{x}_{c,j} - \bar{x}_{c,j}$ | | Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{c,j}(\mathbf{P}_c) - \bar{x}_{c,j}}{\bar{x}_{c,j} - \bar{x}_{c,j}}$ | |
|--|---|----------------------|--|----------------------|--|----------------------|---|----------------------|---|----------------------|
| | 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) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3607 (0.0148) | 2.0746 (0.1204) |
| (b) Replace percentile rank with percent of maximum score attained | 0.0073 (0.0001) | 0.0025 (0.0001) | -0.0008 (0.0002) | -0.0009 (0.0002) | 59.98 (0.09) | 61.08 (0.08) | 3.32 (0.12) | -1.03 (0.11) | 0.2917 (0.0115) | 3.3300 (0.3662) |
| (c) Replace logical reasoning skill with logical-spatial composite | 0.0049 (0.0001) | 0.0020 (0.0000) | -0.0010 (0.0001) | -0.0006 (0.0001) | 46.47 (0.12) | 50.80 (0.12) | 5.16 (0.14) | -2.83 (0.17) | 0.4465 (0.0128) | 2.1017 (0.1069) |
| (d) Include business income in earnings measure | 0.0049 (0.0001) | 0.0016 (0.0001) | -0.0008 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3517 (0.0141) | 2.0898 (0.1203) |
| (e) Age range 35–55 | 0.0049 (0.0001) | 0.0019 (0.0001) | -0.0008 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.4304 (0.0169) | 1.9575 (0.1140) |
| (f) Age range 30–60 | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3705 (0.0151) | 2.0582 (0.1195) |
| (g) Restrict to modal full-year workers | 0.0043 (0.0001) | 0.0016 (0.0001) | -0.0005 (0.0001) | -0.0006 (0.0001) | 49.12 (0.13) | 51.68 (0.14) | 3.95 (0.17) | -3.34 (0.19) | 0.4419 (0.0190) | 1.6945 (0.0833) |
| (h) Extrapolate for ages 35+ | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0008 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3518 (0.0146) | 2.0896 (0.1206) |
| (i) Extrapolate with last age | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3629 (0.0147) | 2.0710 (0.1201) |
| (j) NPV with discount factor 0.93 | 0.0048 (0.0001) | 0.0015 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3329 (0.0143) | 2.1214 (0.1229) |
| (k) NPV with discount factor 0.99 | 0.0048 (0.0001) | 0.0017 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3852 (0.0154) | 2.0334 (0.1181) |
| (l) Quadratic smoothing for estimated skill premium series | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3606 (0.0148) | 2.0748 (0.1203) |
| (m) No smoothing for estimated skill premium series | 0.0050 (0.0001) | 0.0013 (0.0001) | -0.0009 (0.0002) | -0.0006 (0.0002) | 47.96 (0.12) | 50.80 (0.12) | 4.50 (0.16) | -2.83 (0.17) | 0.3015 (0.0257) | 2.1741 (0.1325) |

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, three, and two bootstrap replicates from the calculation of standard errors for rows (b), (c), and (m), respectively, due to values inconsistent with the model. Row (a) reproduces our baseline estimates from Appendix Table 2. Row (b) measures logical reasoning and vocabulary knowledge skills with the percent of the maximum possible test score instead of with the percentile rank. Row (c) 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 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 (d) incorporates business income into our measure of earnings for whom the greatest mode of annual months worked in sample years is less than 12. We are estimating the lifetime skill premia \mathbf{P}_c . Row (e) 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 (h) and (i) vary 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 (j) and (k) vary the discount factor δ that we use in the calculation of \mathbf{P}_c via equation (3). Rows (l) and (m) 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.

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}) | -0.000272 (0.000039) | 0.000613 (0.000592) | 0.002186 (0.001892) |
| Vocabulary knowledge skill (P_{c2}) | -0.000266 (0.000044) | -0.000365 (0.000714) | -0.001618 (0.002049) |
| Number of individuals | | | |
| 1967 cohort | 42,439 | 2,927 | 2,927 |
| 1972 cohort | 45,522 | 3,460 | 3,460 |

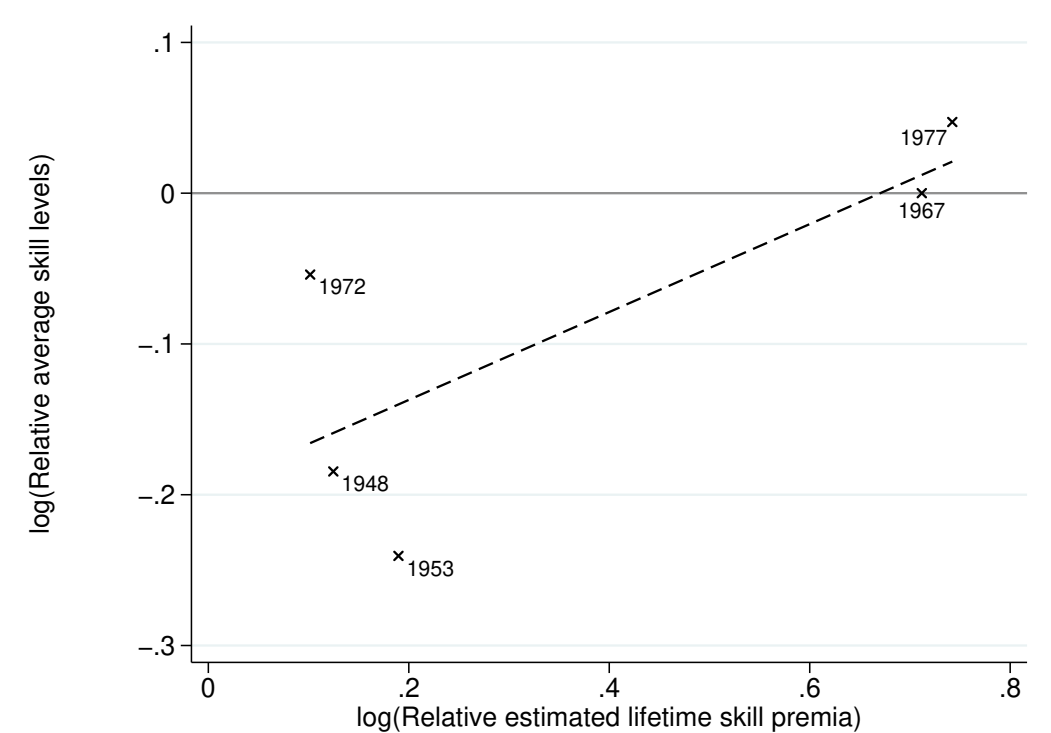
Notes: This table compares the estimated change in lifetime skill premia between birth cohorts 1967 and 1972 based on different estimation methods. The first column is based on the linear trend fitted to the series of estimated lifetime skill premia for the enlistment data, where tests were typically 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 $P_{\ell j}$ | | Change in lifetime skill premium, 1962–1975 $P_{\ell j} - P_{\ell j}$ | | Initial average skill rank, 1962 $\bar{x}_{\ell j}$ | | Change in average skill rank, 1962–1975 $\bar{x}_{\ell j} - \bar{x}_{\ell j}$ | | Share of observed change explained by change in skill premia $1 - \frac{\bar{x}_{\ell j}(\bar{P}_{\ell j}) - \bar{x}_{\ell j}(\bar{P}_{\ell j})}{\bar{x}_{\ell j} - \bar{x}_{\ell j}}$ | |
|---|--|----------------------|--|----------------------|--|----------------------|--|----------------------|---|----------------------|
| | 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) | 47.96 (0.12) | 50.80 (0.13) | 4.50 (0.17) | -2.83 (0.18) | 0.3607 (0.0148) | 2.0746 (0.1204) |
| (b) Age at enlistment (indicators) | 0.0047 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 48.23 (0.12) | 51.08 (0.12) | 3.49 (0.16) | -3.83 (0.18) | 0.4548 (0.0217) | 1.5258 (0.0641) |
| (c) Completed secondary education at enlistment (indicator) | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.28 (0.13) | 50.11 (0.13) | 4.74 (0.17) | -2.60 (0.18) | 0.3394 (0.0137) | 2.2767 (0.1474) |
| (d) Completed secondary education at age 18 (indicator) | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0007 (0.0001) | -0.0007 (0.0001) | 47.16 (0.13) | 49.95 (0.13) | 4.17 (0.17) | -3.18 (0.19) | 0.3839 (0.0171) | 1.8554 (0.0994) |
| (e) log(height) and log(weight) at enlistment | 0.0047 (0.0001) | 0.0015 (0.0001) | -0.0007 (0.0001) | -0.0006 (0.0001) | 47.99 (0.12) | 50.86 (0.13) | 4.64 (0.16) | -2.78 (0.17) | 0.3411 (0.0137) | 2.1642 (0.1206) |
| (f) Non-cognitive skills (standardized within cohort) | 0.0037 (0.0001) | 0.0009 (0.0001) | -0.0009 (0.0001) | -0.0006 (0.0001) | 48.71 (0.13) | 51.55 (0.12) | 4.37 (0.15) | -3.06 (0.17) | 0.2692 (0.0172) | 2.1035 (0.1062) |
| (g) Born outside Sweden (indicator) | 0.0048 (0.0001) | 0.0016 (0.0001) | -0.0008 (0.0001) | -0.0007 (0.0001) | 47.95 (0.12) | 50.80 (0.12) | 4.50 (0.17) | -2.83 (0.18) | 0.3574 (0.0149) | 2.0838 (0.1205) |

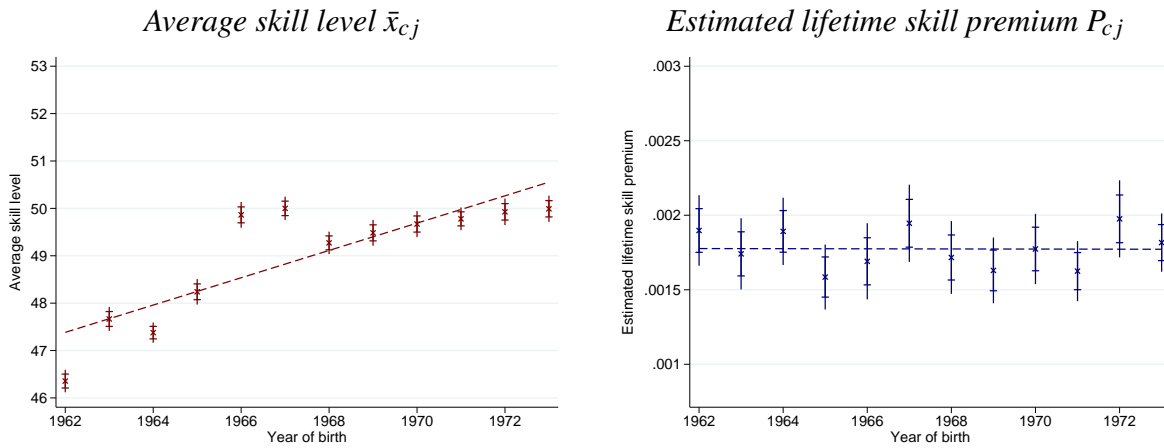
Notes: This table summarizes the sensitivity of our main results to adjusting for different control variables. Standard errors in parentheses are obtained via a nonparametric bootstrap with 50 replicates. In each replicate, for each cohort c , we draw men with replacement from the population in that 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 premia and are used to adjust the estimated average skill levels, following Section 4.4. 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. In specification (f), the measure of non-cognitive skills is standardized to have zero mean and unit standard deviation within each birth cohort.

Appendix Figure 1: Evolution of relative skill levels and relative skill premia, women in survey sample



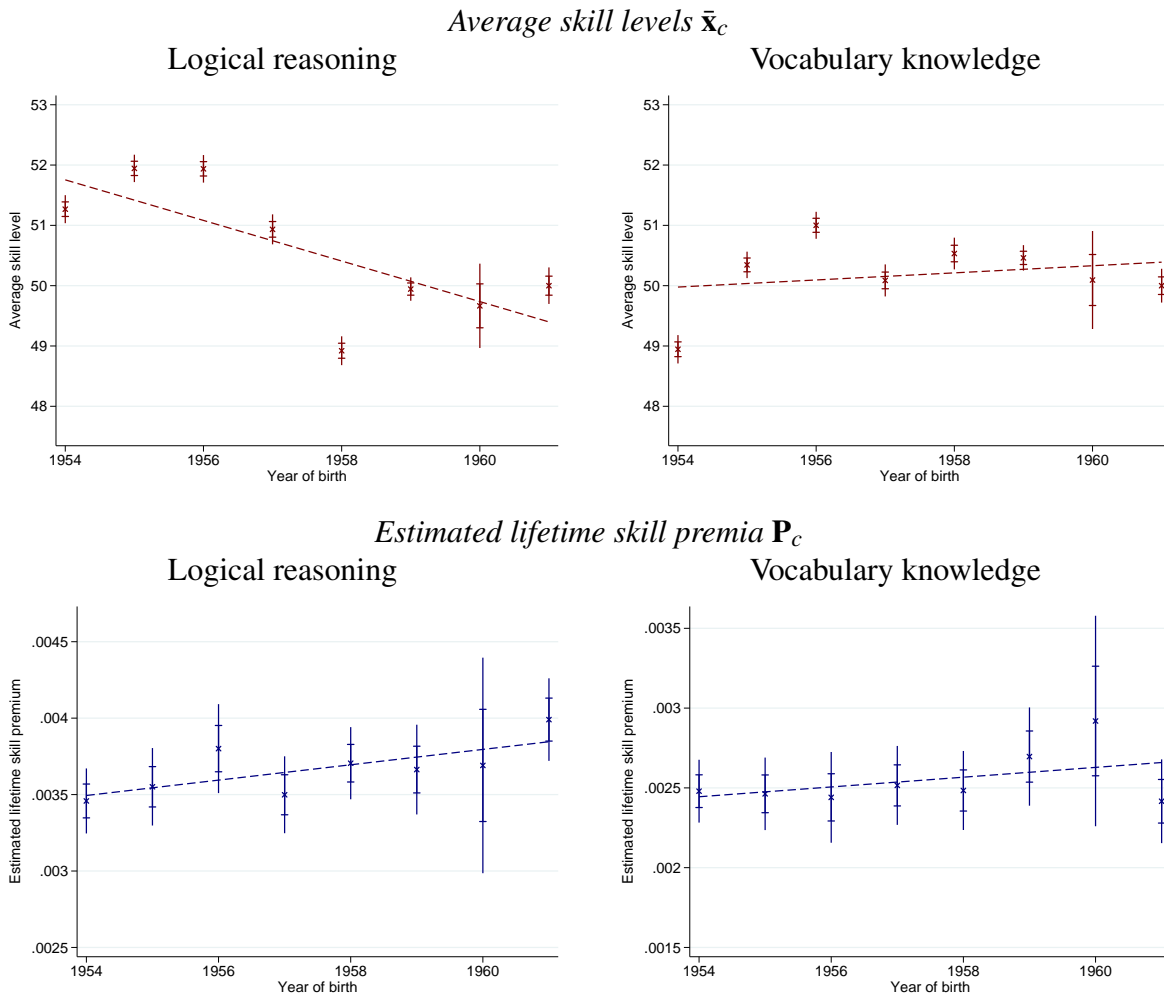
Notes: Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, and 1977, with tests typically taken at age 13, for female respondents. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural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

Appendix Figure 2: Trends in technical knowledge and technical knowledge premia across birth cohorts 1962–1973, military enlistment data



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 technical knowledge test scores for these cohorts. The left plot depicts the average technical knowledge skill $\bar{x}_{c,j}$ 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 $P_{c,j}$ 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 3: Trends in skills and skill premia across birth cohorts 1954–1961, military enlistment data



Notes: 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{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 4: Structure of the survey of parents' perceptions

Panel A: Consent form



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 återropa någon av dessa rättigheter Kontakta Dataskyddsombudet vid Stockholms universitet (dso@su.se).

Mer information om detta finns på Datatillsynens hemsida. <https://www.datatillsynen.se/>

Jag har läst och accepterar villkoren

Jag nekar samtycke

Jag samtycker

Panel B: Survey form



1. Vilket år är du född?

2. Med vilket kön identifierar du dig?

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 löpiskt. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

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 löpiskt. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

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 löpiskt. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

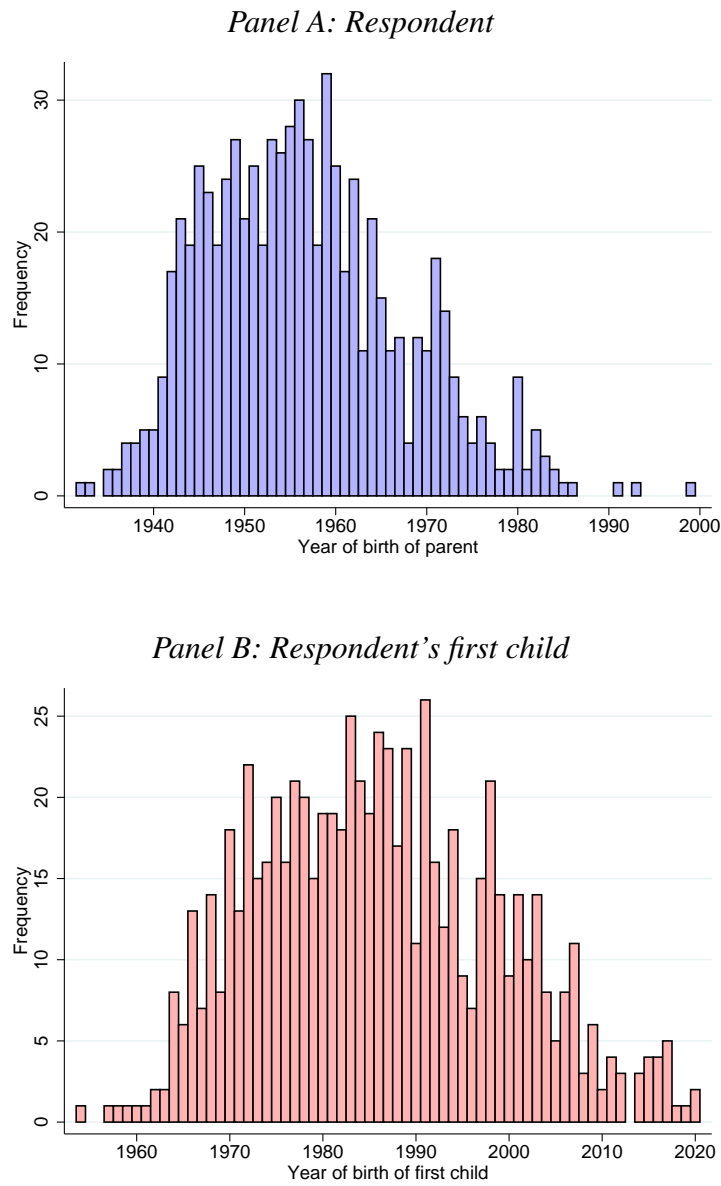
7. Mellan vilka år föddes dina barn? (Markera båda på samma ställe om du bara har ett barn.)

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 löpiskt. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Att kunna komma ihåg fakta, exempelvis definitionen av svåra ord. | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

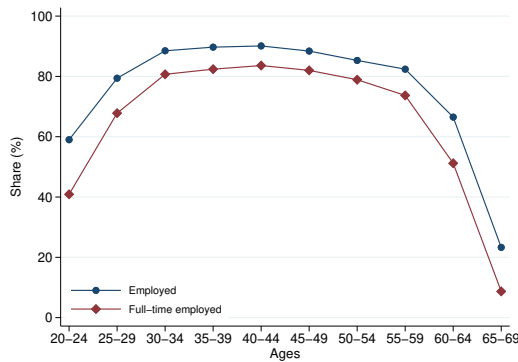
Notes: This figure shows the content and structure of the survey on parents' perceptions described in Section 3.2. Panel A displays the consent form and Panel B displays the survey form, both in the original Swedish.

Appendix Figure 5: Distributions of year of birth of respondent and first child in the survey of parents' perceptions

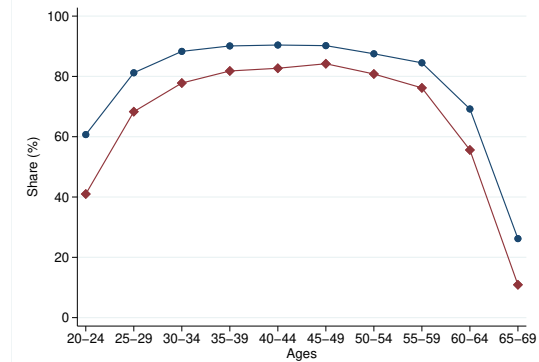


Notes: Data come from the survey of parents' perceptions described in Section 3.2. Panel A shows the distribution of the year of birth of the respondent. Panel B shows the distribution of the year of birth of the respondent's first child.

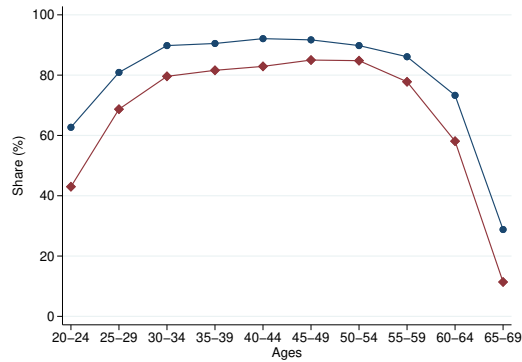
Appendix Figure 6: Male employment rates by age group for selected years



(a) 2010



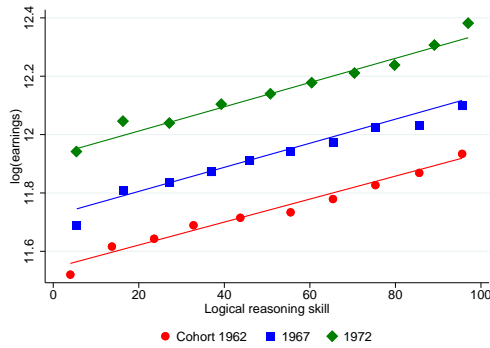
(b) 2015



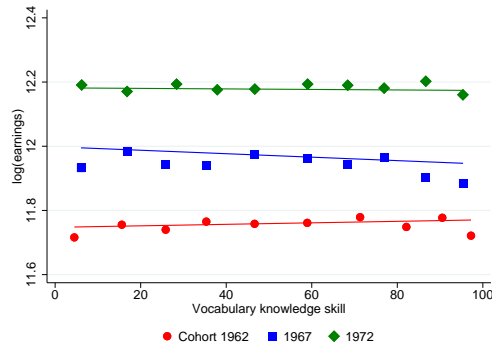
(c) 2019

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 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.

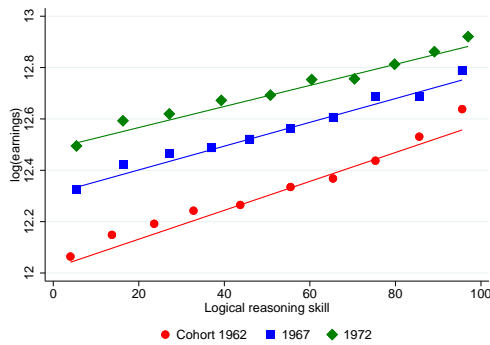
Appendix Figure 7: Illustrating the relationship between log(earnings) and skill percentile, military enlistment data



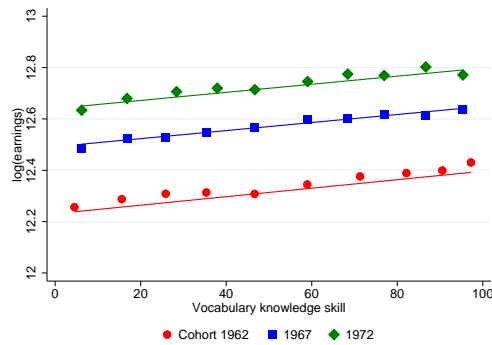
(a) Logical reasoning, age 30



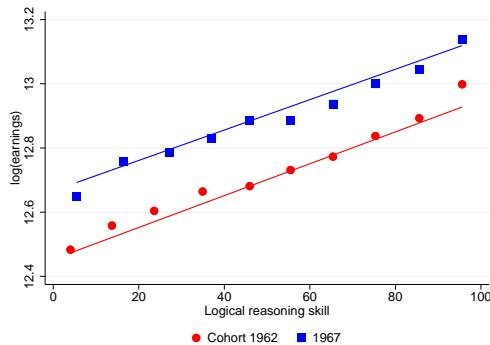
(b) Vocabulary knowledge, age 30



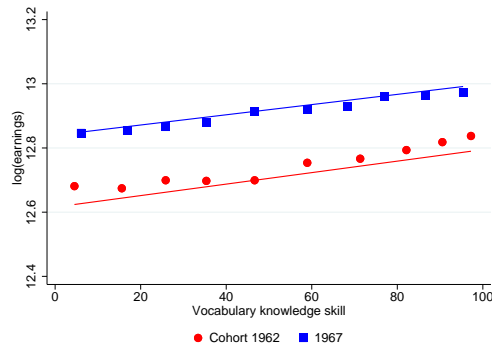
(c) Logical reasoning, age 40



(d) Vocabulary knowledge, age 40



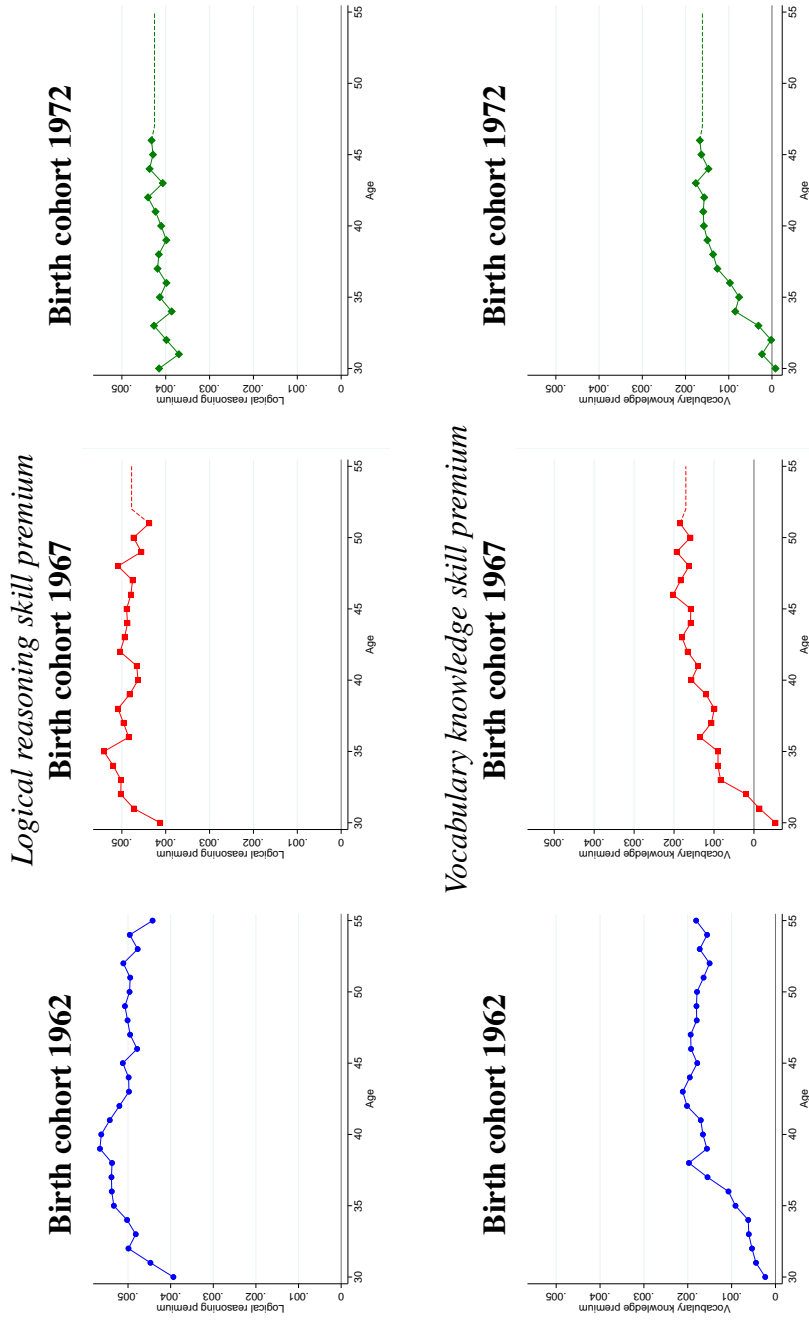
(e) Logical reasoning, age 50



(f) Vocabulary knowledge, age 50

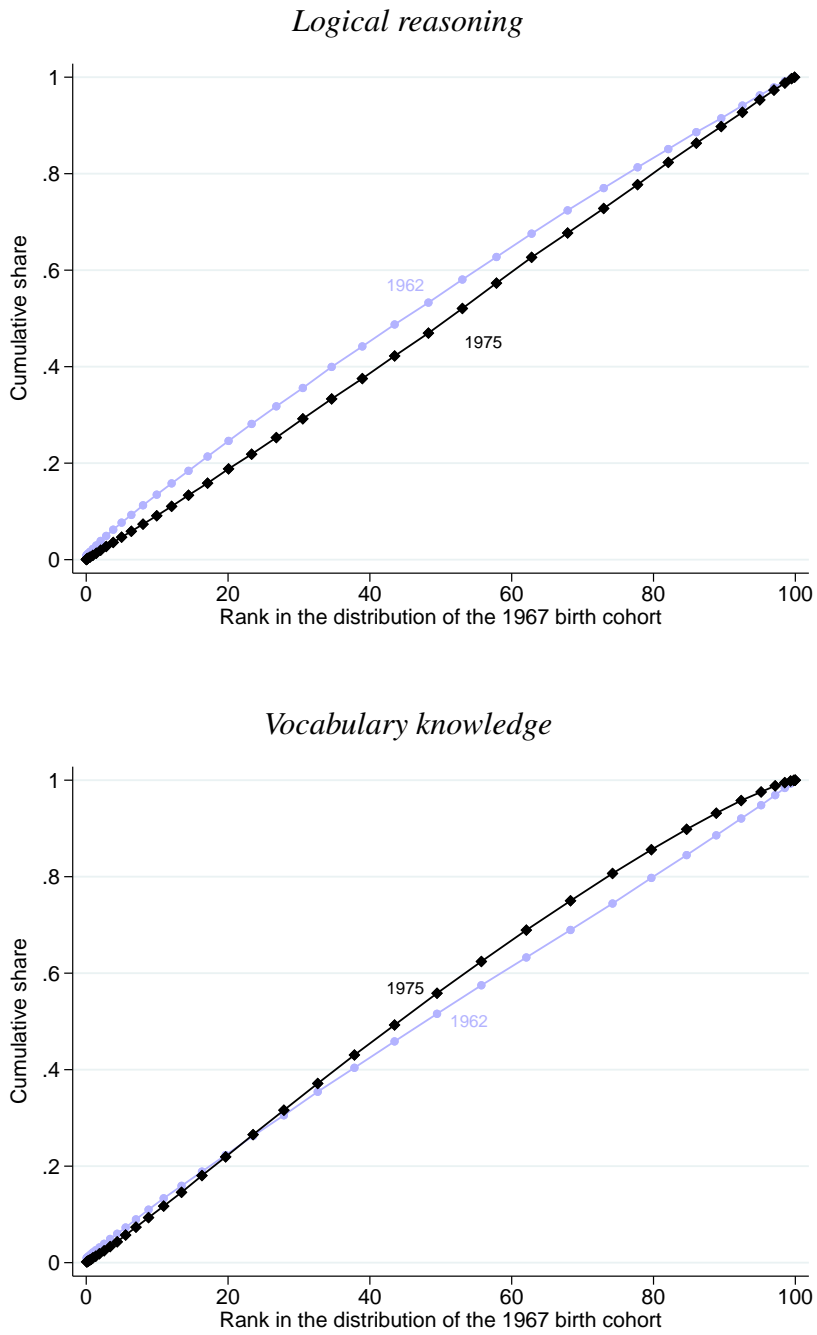
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. This figure illustrates the relationship between the mean of log annual earnings and logical reasoning and vocabulary knowledge skill for birth cohorts 1962, 1967 and 1972,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

Appendix Figure 8: Illustrating the extrapolation of skill premia to ages with no earnings data, military enlistment data



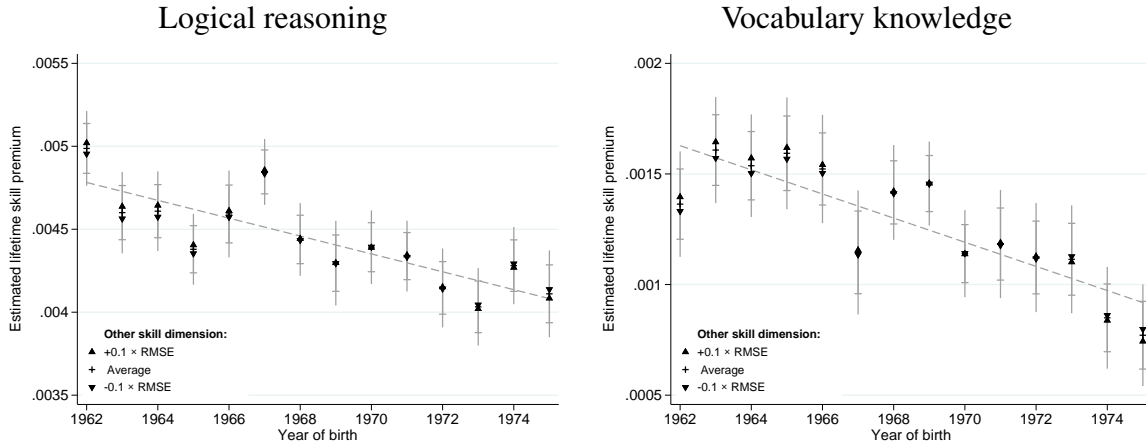
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plots illustrate how we estimate skill premia for ages of working life for which we do not observe earnings. The upper row of plots illustrates for logical reasoning and 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 $\mathbf{P}_{t-t+a,a}$ 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).

Appendix Figure 9: Distributions of skills in the 1962 and 1975 birth cohorts, military enlistment data



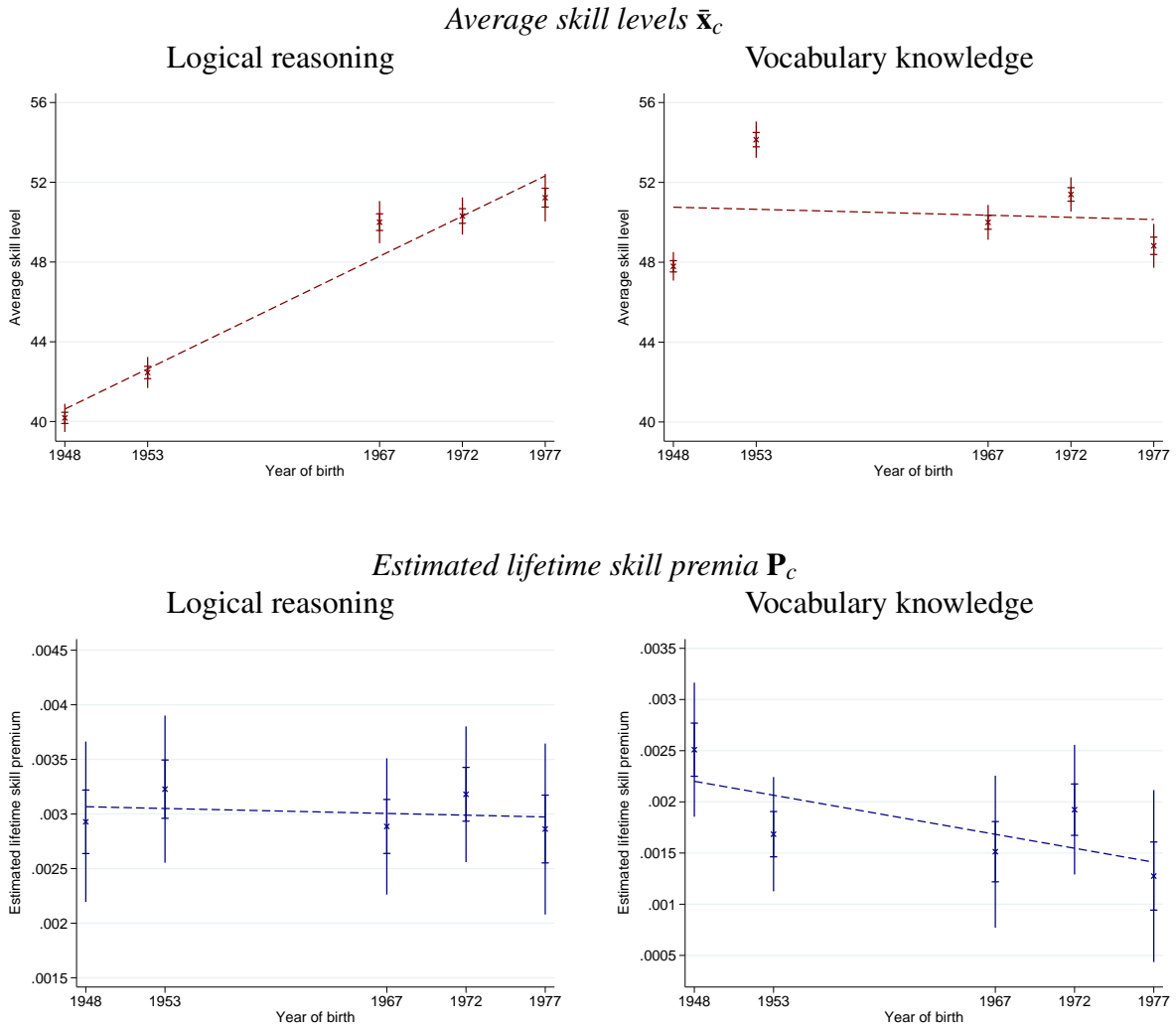
Notes: Data are from the military enlistment sample covering birth cohorts 1962 and 1975, with tests typically taken at age 18 or 19. Each plot depicts the empirical cumulative distribution function of skills x_{ij} for a given dimension j for members i of the 1962 and 1975 birth cohorts. Skills are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

Appendix Figure 10: Trends in skill premia across birth cohorts 1962–1975, allowing for interactions



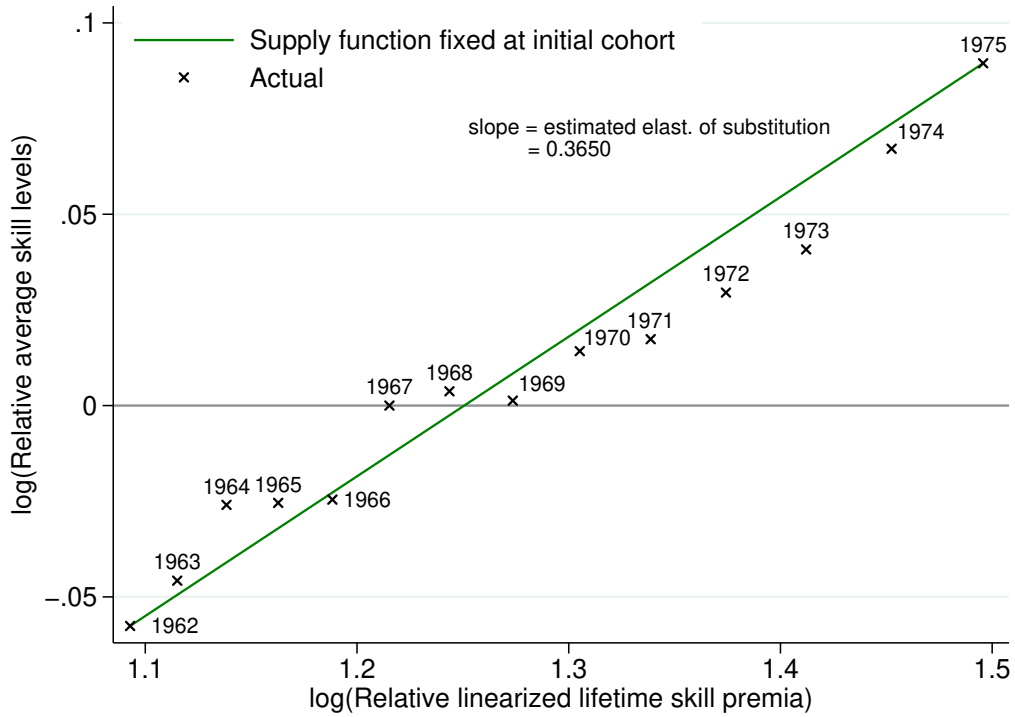
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. We construct the plots as follows. For each cohort c and each year t for which we measure earnings, we estimate a generalization of equation (1) that includes an interaction $x_{i1}x_{i2}$ 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 4.1 to estimate the cohort- and year-specific premia for years outside of our sample, and we compute lifetime premia following equation (3). 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 intervals (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 intervals are computed as sup-t bands following Olea and Plagborg-Møller (2019).

Appendix Figure 11: Trends in skills and skill premia across birth cohorts, survey data



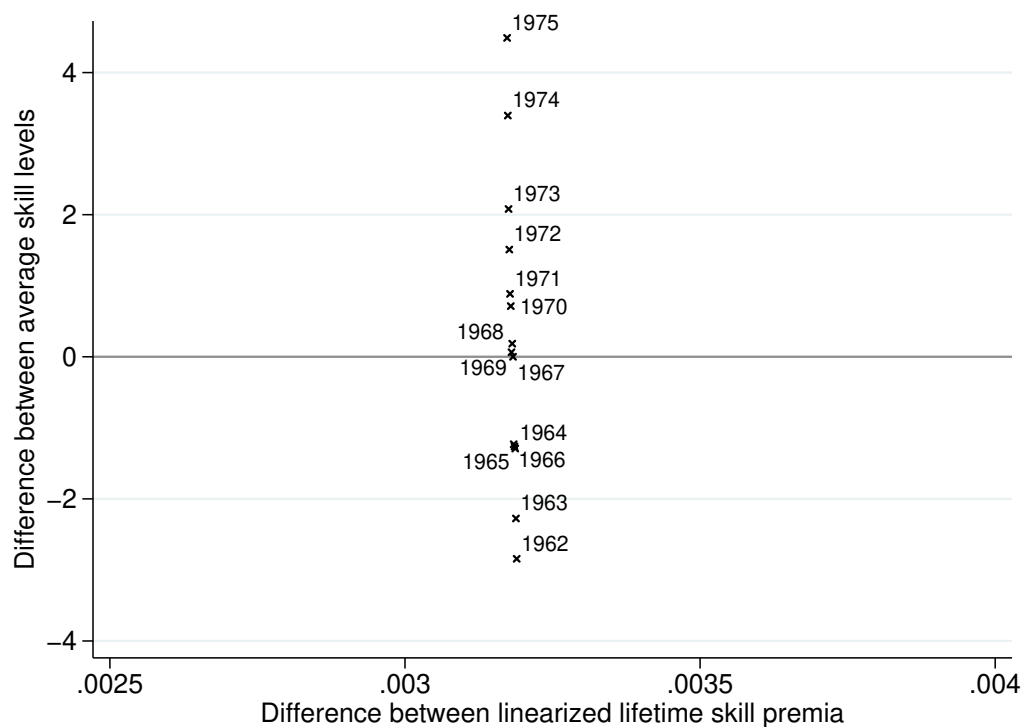
Notes: Data are from the survey sample covering birth cohorts 1948, 1953, 1967, 1972, and 1977. The first row of plots depicts the average skill \bar{x}_c for each birth cohort c . Skills are expressed as a percentile of the distribution for the 1967 birth cohort. The second row of plots depicts the 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 12: Illustration of relative supply function, military enlistment data



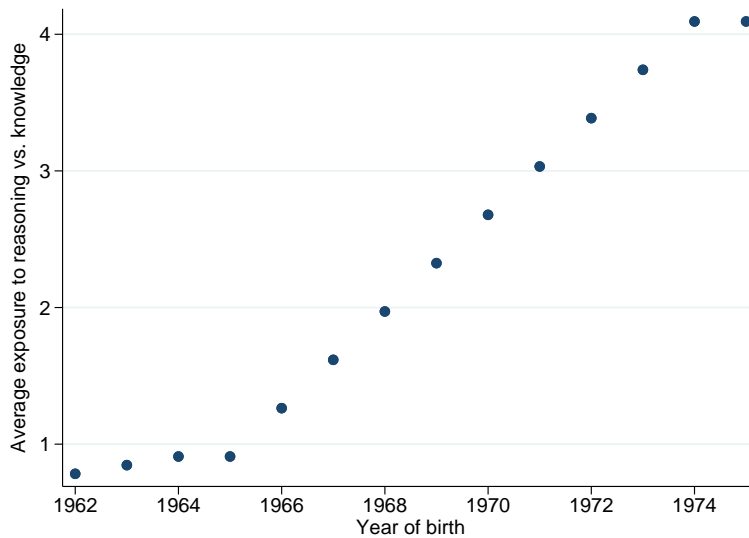
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plot shows a scatterplot of the natural logarithm of the relative average skill level, $\ln(\bar{x}_{c1}/\bar{x}_{c2})$, against the natural logarithm of the relative 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 $\ln(\tilde{x}_{c,1}(\mathbf{P}_c)/\tilde{x}_{c,2}(\mathbf{P}_c))$. The slope of the green line is equal to the estimated elasticity of substitution $\frac{1}{\rho-1}$.

Appendix Figure 13: Differences in skills and differences in skill premia, military enlistment data



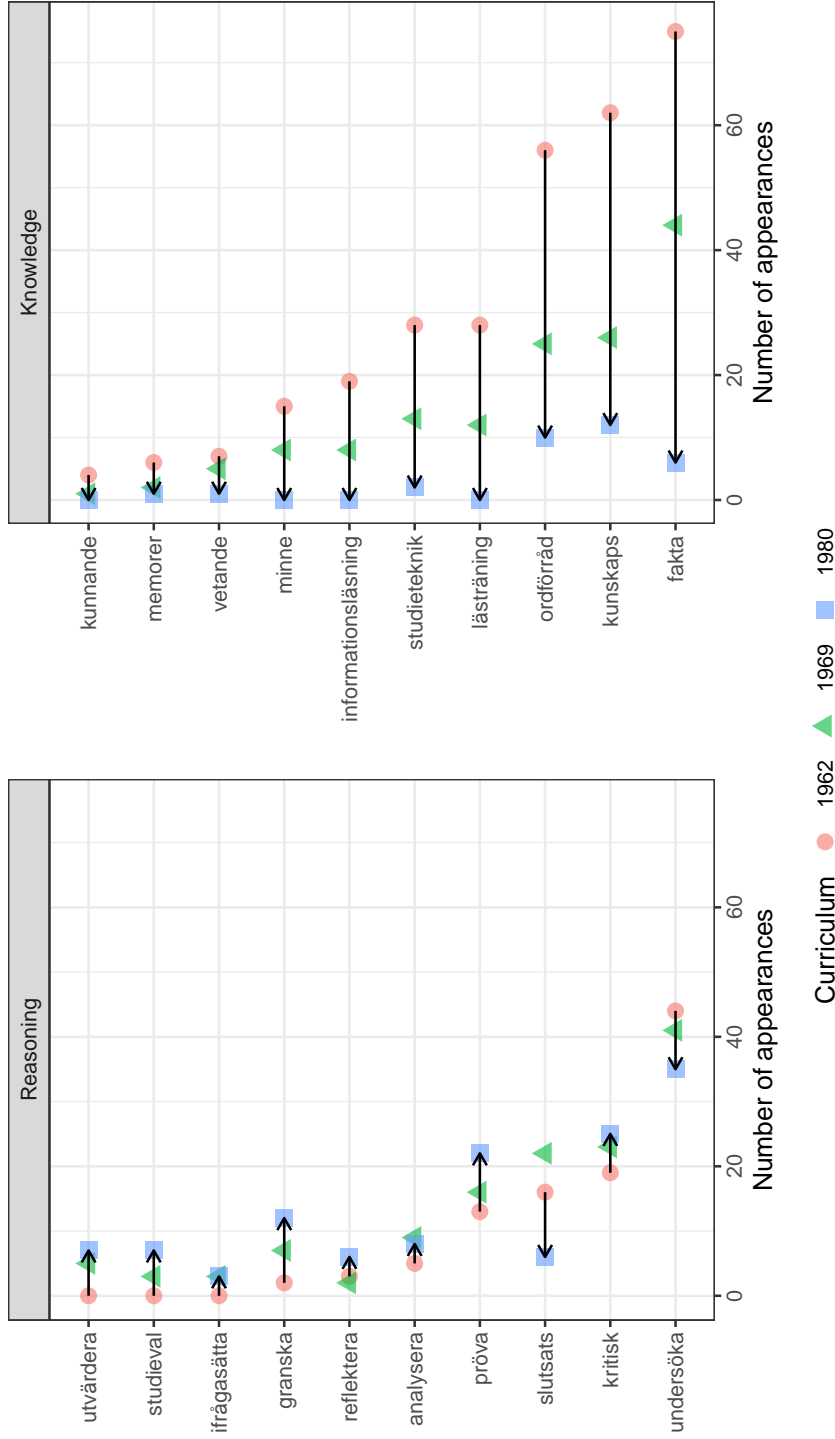
Notes: Data are from the military enlistment sample covering birth cohorts 1962–1975, with tests typically taken at age 18 or 19. The plot shows a scatterplot of the difference between average skill levels, $\bar{x}_{c1} - \bar{x}_{c2}$, against the difference between estimated lifetime skill premia, $P_{c1} - P_{c2}$, based on the linearized skill premia depicted in Figure 1. The ratio of the x-axis range to the x-axis value for the 1962 birth cohort is equal to the analogous ratio in Appendix Figure 12.

Appendix Figure 14: Trends in emphasis on reasoning vs. knowledge in Swedish primary school Curricula



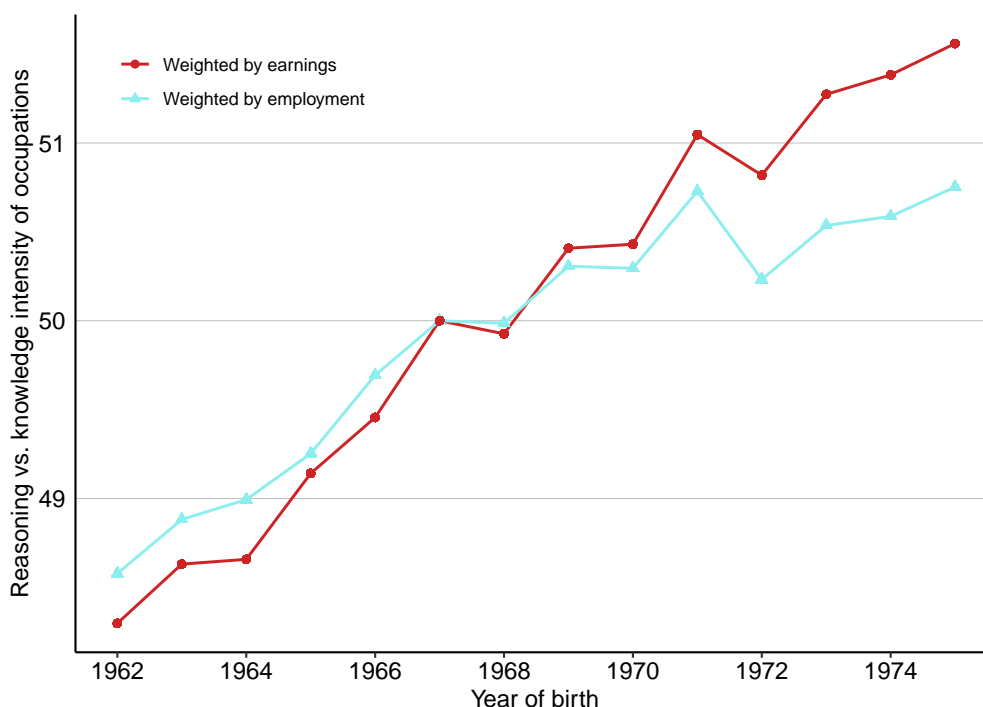
Notes: The plot shows the trend across birth cohorts in the emphasis on reasoning relative to knowledge in the Swedish primary school Curricula (Läroplan for grundskolan) prevailing during the cohort's primary schooling. We construct the series as follows. First, we associate each school year from 1963 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 Appendix Figure 15 for details. Third, for each cohort, we define the average exposure to reasoning vs. 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 age 7 and ending in the spring of the year that members of the cohort turn age 16.

Appendix Figure 15: Selected word families related to reasoning vs. knowledge in Swedish primary school Curricula



Notes: 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). 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 of each word family as follows. For the “analysera,” “studieval,” “granska,” “ifrågasätta,” “informationsläsning,” “kunnande,” “ordföråd,” “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 “lästråning” and “studieteknik” families, we searched for the exact word only. We conducted searches automatically. A Swedish speaker then reviewed search results and excluded cases where usage did not match our intent (e.g., negations).

Appendix Figure 16: Trends in the reasoning vs. knowledge intensity of men’s occupations in Sweden



Notes: The plot shows the trend across birth cohorts in the reasoning vs. knowledge intensity of occupations in the Swedish Occupational Register, measured as the mean percentile rank of the reasoning vs. 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 Occupation Register using data on employment histories from 2004 onwards from Statistics Sweden (2021), 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 vs. 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 vs. knowledge intensity of each Standard Occupational Classification 2010 (SOC 2010) occupation by taking the unweighted average reasoning vs. 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 (2016b) and BLS (2015), manually excluding some matches to improve accuracy. We define the reasoning vs. knowledge intensity of each occupation in the Swedish Occupational Register by taking the employment-weighted mean reasoning vs. knowledge intensity of all corresponding SOC 2010 occupations, using May 2018 OES employment estimates (BLS 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 25.2 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.

D Additional References

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