School vs. Action-Oriented Personalities in the Labor Market*

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Abstract

How do different dimensions of personality predict school vs. labor-market performance? How has the value of these traits changed over time? We answer these questions using data that includes multidimensional personality and cognitive test scores from mandatory military conscription for approximately 80% of Finnish men. We document that some dimensions of noncognitive skills are productive at school, and some dimensions are counterproductive at school but still valued in the labor market. Action-oriented traits (activity, sociability and masculinity) predict low school performance but high labor market performance. School-oriented traits, such as dutifulness, deliberation, and achievement striving, predict high school performance but are not independently valued in the labor market after controlling for school achievement. We further document that the labor-market premium to action-oriented personality traits has rapidly increased over the past two decades. To interpret the empirical results, we outline a model of multidimensional skill specialization. The model and evidence highlight two paths to labor-market success: one through school-oriented traits and formal skills, and one through action-oriented traits and informal skills.

Keywords: Multidimensional skills, cognitive skills, noncognitive skills, personality, stereotypes, work, labor market, education.
JEL Codes: I20, I24, J01, J24, J31

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1 Introduction

Extensive evidence shows that noncognitive skills[1] improve labor market success (Almlund et al., 2011; Deming, 2017), but the channel is incompletely understood. Some studies show that noncognitive skills affect labor-market performance indirectly through higher educational aptitude (Cunha & Heckman, 2007), while other studies emphasize that noncognitive skills affect labor productivity directly at work (Deming, 2017).

How do different dimensions of personality predict school vs. labor-market performance? How has the labor-market value of these traits changed over time? We answer these questions using globally exceptional data that includes multidimensional personality and cognitive test scores, education, and labor-market records for 79% of Finnish men born 1962–1979 (n = 489,252). The personality and cognitive test data were collected by the Finnish Defence Forces during mandatory military service.

This paper shows that some dimensions of noncognitive skills are productive at school and also valued in the labor market, while other dimensions are counterproductive at school yet still valued in the labor market. We further document that the labor-market returns to action-oriented personality traits (traits that predict low school performance) have rapidly increased over the past two decades. Conversely, the economic returns to school-oriented traits have declined sharply.

Consider the school versus the labor-market. Noncognitive skills related to conscientiousness have been shown to predict school achievement (Almlund et al., 2011). At the same time, the common stereotypes of socially awkward 'nerds' and outgoing 'jocks' suggest an inverse relationship between school achievement and particular dimensions of noncognitive skills.[2] High achievers in school may lack at least in some dimensions of economically valuable personality traits, and conversely, low-achieving students may have some redeeming qualities that compensate in the labor market for their lack of academic success. In short, this idea suggests a negative association between academic performance and outward-oriented social skills.

We present four new descriptive facts. First, we document that one subset of personality traits positively predicts school achievement, but another critical subset of personality traits negatively predicts school achievement. These subsets follow the common stereotypes: men, who score highly in activity-energy, sociability, and masculinity, tend to perform worse in standardized tests. We label this component as action-oriented traits. The label also reflects the source of measurement: The Finnish Defence Forces

[1] Noncognitive skills are typically defined as all skills not predicted by cognitive test scores. In some contexts, noncognitive skills specifically refer to socioemotional skills. We adopt the standard definition that noncognitive skills refer to all potentially economically valuable traits that the cognitive tests do not measure. In this view, we define some personality traits as noncognitive skills.

[2] Stereotype accuracy is one of the most replicable findings in social psychology (Jussim et al., 2016). Both stereotypes we mention can have negative connotations when referring to a person.

values these traits positively. In contrast, dutifulness, deliberation, achievement striving, self-confidence, and leadership predict good school performance; we label this component as school-oriented traits.

Second, the traits that predict low school achievement still predict labor-market success. One standard deviation increase in action-oriented traits predicts a 5-log point increase in earnings at age 35. The school-oriented traits also strongly predict labor-market success. But the school-oriented traits are not independently valued in the labor market: their predictive power on labor-market performance becomes near zero after controlling for school achievement.

Third, we find that the labor-market returns to action-oriented traits that predict low school performance have rapidly increased over the past 17 years, from 0 to 8 log points per standard deviation. Men with high activity-energy, sociability, and masculinity measures (but with low mathematics skills) experienced the highest earnings gains between 1997 and 2017. The returns to school-oriented traits have declined from 13 to 7.5 log points.

Fourth, specialization of skills has increased over the past two decades: men are more likely to have either high mathematics skills or action-oriented traits and are less likely to have both.

To understand the empirical results, we outline a model of multidimensional skill specialization. Intuitively, the model highlights two paths to labor-market success: one through school-oriented traits and formal skills, and one through action-oriented traits and informal skills. In the model, the labor market rewards individuals for their formal skills gained through education and for their informal skills, e.g., initiative, social skills, and charisma. Personality is a fixed endowment for an individual, but skills are endogenous and require a time investment. At the investment stage, individuals can allocate their time between study and activities that improve their informal skills, such as social life. We model personality by two separate dimensions: traits that increase productivity in informal-skill formation (action-oriented) and traits that make studying more efficient (school-oriented). Heterogeneity in the initial endowment of traits generates a comparative advantage in formal or informal skill accumulation. In equilibrium, this comparative advantage drives individuals to specialize relatively more in the type of human capital where they have pre-existing tendencies.

We interpret the findings using the model. First, we demonstrate that both the action-oriented and school-oriented personality traits have a positive return in an earnings regression. But controlling for standardized test scores, the return for action-oriented traits increases, and the return for school-oriented traits becomes small. This pattern arises from the intransitivity of correlations between action-oriented traits, test scores, and adult earnings. Our model rationalizes this intransitivity: higher endowment in action-oriented traits increases investment in informal skills at the expense of school success. Since test-score performance is endogenous, its inclusion inflates the returns to action-oriented traits and deflates the returns to school-oriented traits. Our model allows traits to directly affect earnings beyond their instrumental effects through informal and formal skills (e.g., education). Looking through our model, the low returns to school-oriented traits when test scores are included suggest that their effect would mostly be mediated by educational achievement. We cannot similarly disentangle the direct effects of action-oriented traits from the returns to informal skills because we cannot directly measure informal skills. Therefore, in our empirical work, a single variable captures both the direct effect of action-oriented traits and the indirect effects through informal skills.

Next, we explore the channels through which the returns are realized in the labor market by estimating a model where personality traits and test scores explain different response variables. The traits that predict high school achievement (school-oriented traits) appear to affect labor-market performance mainly through occupational sorting, and the traits that predict low school achievement (action-oriented traits) primarily through within-occupation effects and work experience. On average, action-oriented individuals are not more likely to select into high-paying occupations. Instead, action-oriented individuals acquire less education and start their careers earlier but with fewer unemployment spells. Specifically, they are less likely to select into high-paying professional occupations, typically not available without higher education. But even with lower education, they are more likely to end up in a managerial position. In contrast, individuals with high school-oriented traits are more likely to select into high-paying professional occupations. They acquire higher education, start their careers later, and spend less time in unemployment. Occupational and educational sorting explains a large part of earnings variations for both types of individuals. But when including fixed effects for education and occupation, action-oriented traits become a significantly larger predictor of earnings than mathematics. In total, we interpret this as evidence that action-oriented traits improve earnings, mainly through experience, job performance, and/or career progress. In contrast, personality that predicts higher educational attainment helps individuals start their careers in higher-paying jobs but plays a smaller role afterward.

Finally, we document two novel time trends. First, the return to action-oriented traits has increased markedly during our 17-year measurement period. The finding is consistent with earlier studies on the returns to social skills (Deming, 2017) and non-cognitive skills (Edin et al., 2021). But it also provides a new angle: We observe a similar rise to other action-oriented traits—activity and masculinity. At the same time, the returns to traits that predict school-performance have declined. Second, specialization into two distinct types has become more common: more students have either low mathematics and high action-oriented traits *or* high mathematics and low action-oriented traits. In our model, these trends are consistent with a supply-side response, where the increasing returns to informal skills reinforce the skill specialization.

This paper contributes to several distinct lines of research.

Multidimensional skills. Re-emerging literature highlights the importance of the multidimensional nature of skills. The idea that skills are multidimensional is not new. For example, the classic Roy (1951) model formalizes the idea that workers may differ in their types of skills (hunting vs. gathering), and that this affects the optimizing choices of workers selecting between bundles of tasks. Gardner (1983) differentiates skills into specific 'modalities,' imperfectly described by a unidimensional skill.

An emerging line of economic research, both empirical and theoretical, focuses on the multidimensional match between skills and tasks (Guvenen et al., 2020; Lise & Postel-Vinay, 2020; Fredriksson et al., 2018; Lindenlaub, 2017; Gathmann & Schönberg, 2010; Groes et al., 2015). These studies emphasize the potential for skill mismatch: a situation where worker's bundle of skills is not well-matched with the distribution of skill-requirements for the set of tasks.

This paper provides novel descriptive facts to advance this literature. It illustrates skill specialization in the supply side of multidimensional skills. We document that this specialization has concrete implications on occupational sorting and earnings.

Noncognitive skills. A large literature analyzes the role of noncognitive skills in the labor market. The evidence unambiguously demonstrates that a wide array of noncognitive skills—personality traits, interpersonal skills, etc.—are important drivers of labor-market success (e.g., Heckman et al. 2006; Lindqvist & Vestman 2011; Weinberger 2014; Deming 2017; Jokela et al. 2017).[3] The research on noncognitive skills emphasizes two channels on how noncognitive skills may affect labor-market performance: the direct channel, for example, social skills facilitating teamwork in production (e.g., Deming 2017), and the indirect channel, for example, noncognitive skills fostering cognitive skills and human-capital production (e.g., Cunha & Heckman 2007; Borghans et al. 2016).

We complement this literature by showing that the noncognitive skills associated with the indirect channel are notably different from those associated with the direct channel. That is, the traits that predict good school performance are different from those that predict good labor-market performance (e.g. conscientiousness vs. extraversion). In particular, we show that social skills—while important in the labor market, e.g., for teamwork (Deming, 2017)—are negatively correlated with academic test-scores.

[3] Almlund et al. (2011) provide an excellent survey of the evidence on the predictive power of personality in the labor market.

In this line of work, the most closely related research are Levine & Rubinstein (2017) who show that the inverse 'combination of 'smart' and 'illicit' tendencies as youths' predict entry into and success in entrepreneurship, Papageorge et al. (2019) who argue that some childhood misbehavior represents socio-emotional skills that are valued in the labor market, Lleras-Muney et al. (2020) who analyze the dual decision of investment in education and social capital, and Bursztyn et al. (2019) who highlight the trade-off between social-image concerns and school effort.

Education. Our findings provide an explanation to the 'reading penalty paradox' documented by Altonji et al. (2016) and Sanders (2015). Frequently-used US data sets that include information on test scores and earnings exhibit a negative association between reading scores and earnings once the researchers control for mathematics test scores. This pattern also arises in our data. But it goes away once we control for personality traits. The predictive returns to verbal skills are close to zero with personality controls. These pieces of evidence suggest that the observed 'reading penalty' emerges from omitted economically valuable noncognitive skills that are negatively correlated with verbal skills.

Trends in returns to skills. Long-standing literature estimates the returns to skills over time (Katz & Murphy, 1992; Goldin & Katz, 2008; Acemoglu & Autor, 2011; Beaudry et al., 2016; Deming, 2017; Edin et al., 2021). We show that the returns to those skills that predict low school performance, sociability, activity, and masculinity, have rapidly increased over the past 17 years in Finland. At the same time, the returns to cognitive skills has been remarkably stable. In the supply side, we show that the skill specialization, to school-oriented traits and formal skills and to action-oriented traits and informal skills, has increased over the past 17 years.

2 Data

This project combines several data sources using unique person identifiers.[4]

Personality and Cognitive Skills Data for personality and cognitive skills are obtained from the *Finnish Defence Forces* (FDF), which has tested all military conscripts since 1955. The available data cover 79% of Finnish men born between 1962 and 1979 (n = 489,252).

The data provide detailed test scores for personality (8 dimensions) and cognitive skills (3 dimensions). The measured personality traits are: sociability, activity-energy, masculinity, dutifulness, deliberation, achievement motivation, leadership motivation, and self-confidence. The measured cognitive skills are visuospatial, arithmetic, and

[4]The data are described in more detail in Appendix A.

verbal reasoning. The visuospatial test is similar to Raven's Progressive Matrices (Raven et al. 2000).

The personality dimensions are based on the Minnesota Multiphasic Personality Inventory (MMPI) which predates the Big Five model by several decades. That is why it includes a somewhat different set of items compared to the Big-Five inventory. However, two of the Big-Five traits are represented by their facets (subtraits). Dutifulness and deliberation are subtraits associated with conscientiousness, whereas the subtraits sociability, activity-energy and self-confidence are associated with extraversion. Masculinity is not measured in all standard personality inventories but turns out to be an important predictor in our analysis.

Military conscription in Finland is universal and grants relatively few exceptions. Finnish men are drafted in the year they turn 18 and most start their service at age 19 or 20. Military service lasts for 6–12 months, and most conscripts do not continue service at the military. FDF uses psychological tests to assess conscripts' suitability for non-commissioned officer training.

Both personality and cognitive ability tests are typically taken in the second week of military service in a 2-h paper-and-pencil format in standardized group-administered conditions. The personality test contains 218 statements with a response scale of yes/no. The cognitive test contains 120 multiple-choice questions. The test questionnaires have been unchanged for the timeline of the study, and the scores are designed to be comparable across cohorts. Appendix A includes a more detailed description of the FDF data.

Education Data on education come from three sources.

The Register of Completed Education and Degrees contains exact information on the educational degrees the individual has obtained, including both the level and field, and the date at which the degree was granted. All degrees completed in Finland are generally recorded in these data.

The Secondary Education Application Register contains information on the 9th-grade transcript, including the GPA. The data are produced as a side product of the centralized application system for secondary education maintained by The Finnish National Board of Education (FNBE). While the 9th-grade records are only partly from national standardized tests, the middle schools in Finland are all public and have low quality variance. Attendance of the 9th grade is near-universal. These data are only available for cohorts born 1975-1979.

Finnish Matriculation Examination Board Register (FMEB) contains test-score data by academic subject in the standardized national-level high-school exit examination, The Matriculation Examination (ME). Independent reviewers grade the test in a double-blind manner, and within the timeline of this study, the test scores directly correspond to ranks within a subtest and cohort. The students choose a minimum of four 6-hour tests in their first language, foreign language, mathematics, and in the subjects of humanities and natural sciences. The first-language test is mandatory. Language and mathematics tests have basic and advanced-level versions. When needed for the analysis, we map the mathematics test scores into a single dimension by weighting the advanced and basic test scores using their predictive power on the military arithmetic test.[5] As an institutional background, secondary schooling in Finland has two tracks: academic and vocational. Participation to the academic track increased from 35% to 47% between birth cohorts 1962–1979. ME is the academic track's exit exam. A similar standardized test does not exist for the vocational track. ME test scores are partly used in university admissions (most university admissions, however, were based on a separate admissions exam), but they do not play a meaningful independent role in the labor market. The Finnish school system contains relatively few extracurricular activities (such as sports teams) that could be used to measure non-school human capital, and the participation or performance in these activities are generally not recorded.

Labor Market and Demographics The project uses detailed longitudinal register data on the full Finnish population compiled by *Statistics Finland* from multiple sources.

The register data provide information on demographics, labor market status, earnings, occupation, industry, firm and establishment identifiers, county of residence and birth, and the identity of parents and siblings, for all Finnish residents.

Income data are obtained from the *Finnish Tax Authority*. We measure 'prime-age' earnings as the average annual labor-market earnings during ages 35–38. We deflate all values to 2010 Euros using the Statistics Finland CPI.

Main Estimation Sample Our main estimation sample consists of the intersection of individuals with valid (1) military test scores, (2) high school exit exam records, and (3) positive prime age earnings (over 99%). The sample size is approximately 158,000 containing about 80% of male high school graduates born in 1962-1979. Potential selection issues are discussed in Appendix A.

For our main analysis, we use logarithmic earnings. Figure 1 shows their distribution in our main sample. The long left tail typical for log earnings distributions can raise concerns about outliers driving our OLS results. These concerns are addressed in section 4 and Appendix C.

[5] This procedure is described in more detail in Appendix A.

3 Model

In this section, we develop a simple model of multidimensional skill specialization that provides a structure for the relationships between personality, education, and labor-market performance.[6] We focus on the distinction between the production of human capital and the productive activities in the labor market. The personality traits are viewed as a fixed type and skills are viewed as endogenous. For concreteness, the context can be thought as students in high school and the labor-market.

At the center of the model, there are two production functions for two types of human capital, formal skills ('education', H) and informal skills ('social capital', S),[7]

$$H(h; N, J) = a(N, J) \times h \tag{1}$$

$$S(s; N, J) = b(N, J) \times s \tag{2}$$

Formal skills H are produced by time investment h ('studying') and informal skills S are produced by time investment s ('socializing'). The productivities of human capital production, a and b, depend on the endowment of personality traits (N for 'school-oriented' and J for 'action-oriented').

In making a decision, the students face a time-allocation constraint:

$$h + s = T. \tag{3}$$

Time spent on studying is away from time spent on socializing. We normalize the time endowment as $T = 1$.

The objective function is:

$$U(s; N, J) = H(1 - s; N, J) + S(s; N, J) + V(s; N, J) \tag{4}$$

The students value both types of human capital, H and S, but also derive direct utility (or dis-utility) from studying and socializing, V, that depends on their endowment of traits.[8] We further assume that the direct utility function depends only on the relative allocation between h and s.[9]

[6] The model is adapted from Lleras-Muney et al. (2020).

[7] For simplicity, we consider two 'technologies of skill formation' (Cunha & Heckman, 2007). The case for n technologies is analogous.

[8] If U reflects log utility, the objective function arises under the canonical CES preferences. At this point, to keep the notation clear, we abstract from potential return multipliers for H and S in the objective function.

[9] Because time is spent between studying and socializing, V captures all direct costs/benefits of studying/socializing. For example, action-oriented students could dislike studying but school-oriented students might enjoy it.

Students choose how much time to spend on socializing (s) to maximize the objective function under the constraint. With no strategic behavior or dynamics, the optimal time-allocation decision between studying and socializing is a static individual optimization problem.[10] The first-order condition for socializing is:

$$\frac{\partial V(s; N, J)}{\partial s} = a(N, J) - b(N, J) \tag{5}$$

$$s^*(N, J) = g_s(a(N, J) - b(N, J); N, J) \tag{6}$$

where g_s is the inverse function of $\partial V(s, N, J)/\partial s$ with respect to s. For an interior solution to exist, Expression 5 must be positive. Intuitively, if at the optimal s^*, socializing is not only more fun ($\partial V(s; N, J)/\partial s > 0$) but also more productive ($b(N, J) > a(N, J)$), there would be no reason to study at all.

The theoretical analysis focuses on the decision to socialize, s; the analysis for the inverse decision of studying, $h = 1 - s$, is symmetric. We provide proofs in Appendix B.

This setup provides some flexibility by admitting at least three distinct interpretations. In the classic view, students gain utility from formal skills H and informal skills S because there is a return to different human-capital types in the labor market. Students also face a direct cost or benefit from studying and socializing V that depends on their endowments. In this view, socializing is an investment: students socialize not just because studying may be laborious but also because socializing builds people-skills and networks rewarded in the labor market.

From a more modern perspective (see, for example, Lavecchia et al. 2016), students might not be sufficiently forward-looking to consider their future earnings. However, the terms H and S can be interpreted as social norms that guide their choices, for example, through parental pressure. In this interpretation, the cost function V is the direct utility of socializing over and above the social-norm component S.[11]

Finally, we could abstract entirely from the source of utility derived from either type of human capital *stock*. Students simply enjoy the activity of spending time s with their friends. Performing well in tests requires time to study (h), which may be uninteresting and incurs a cost $-V$. From this perspective, V reflects the direct utility of time spent socializing, which may be different for students with different personality endowments.

[10] The model has an implied timing that corresponds to a typical path from adolescence to adulthood. Students enter a schooling period with an initial personality endowment (N, J). They then decide how much time to spend on socializing s. Their H and S are realized at the end of the schooling period. After the schooling period, they enter the labor market and receive earnings Y.

[11] The cost of studying and the direct utility of socializing mirror each other, because students allocate time T between the two.

Skill Specialization The fundamental trade-off between time investments in this model leads to skill specialization, where students with a comparative advantage in the action-oriented endowment invest more time on socializing relative to students with a comparative advantage in the school-oriented endowment. Taking a derivative of the first order condition in Equation 5 and solving for $\partial s^*(N,J)/\partial J$ gives:

$$\frac{\partial s^*(N,J)}{\partial J} = -\left[\underbrace{\frac{\partial^2 V(.)}{\partial s^2}}_{<0}\right]^{-1}\left[\underbrace{b^J(N,J) + \frac{\partial^2 V(.)}{\partial s \partial J}}_{\text{marginal benefit of } \Delta J} - \underbrace{a^J(N,J)}_{\text{marginal cost of } \Delta J}\right] > 0. \qquad (7)$$

The first term is the gradient in the marginal direct utility of socializing (or marginal cost of studying). We assume the standard decreasing marginal utility. Hence, for socializing: $\partial^2 V(.)/\partial s^2 < 0$. We also assume that the productivity of informal-skill accumulation $b(N,J)$ is increasing in the action-oriented trait-endowment J. This assumption is based on the idea that learning social skills, creating networks, and improving their social hierarchy position is easier for students who already have sociable and proactive personalities. Likewise, we assume that action-oriented students enjoy a larger marginal utility of socialization s. Formally, $\partial^2 V(.)/\partial s \partial J > 0$. This reflects the idea that the opportunity cost for studying is higher for action-oriented students who could be having fun with their friends instead. Finally, we assume that productivity of studying, $a(N,J)$, does not depend on the action-oriented trait, so that $a^J(N,J) = a^J(N) = 0$. With these key assumptions, the right-hand side of Equation 7 is positive, and an increase in the action-oriented endowment leads to an increase in the time spent socializing.

Immediately following from these assumptions we also have:

$$\frac{\partial H(1-s;N,J)}{\partial J} = \frac{\partial a(N)(1-s^*(N,J))}{\partial J} = -a(N)\frac{\partial s^*(N,J)}{\partial J} < 0. \qquad (8)$$

In other words, conditional on the school-oriented trait N, more action-oriented students have worse test scores. It implies that comparative advantage determines the time-allocation decision.

Figure 2 simulates the model with a quadratic cost function and linear productivity functions. Each line represents an isoquant where the optimal time allocation decision s^* does not change. Along each line, as long as the *comparative* proportion of endowments does not change, the *absolute* levels can vary substantially, still resulting in the same optimum allocation. For example, at the bottom right-hand corner, investment in s is highest; these are students who are high in J but low in N. At the upper left-hand corner are students high in N but low in J; their investment in s is lowest.

Returns to Personality The labor market rewards both types of human capital, H and S, and also directly the endowments, N and J. Earnings are determined by:

$$Y = r_H H(1-s; N, J) + r_S S(s; N, J) + r_N N + r_J J \tag{9}$$

$$= r_H a(N)(1-s^*(N,J)) + r_S b(N,J) s^*(N,J) + r_N N + r_J J \tag{10}$$

where r_H and r_S are the returns to the respective dimensions of human capital and r_N and r_J are the direct returns to the respective traits.

The marginal returns to the action-oriented trait are:

$$\frac{\partial Y}{\partial J} = \underbrace{r_S b^J(J,N) s^*(N,J) + r_J}_{\text{direct effect of } \Delta J} + \underbrace{(r_S b(J,N) - r_H a(N))}_{\text{net earnings change for } \Delta s} \underbrace{\frac{\partial s^*(N,J)}{\partial J}}_{\Delta s} \lesseqgtr 0. \tag{11}$$

The first term is the direct effect: the effect of the increase in the productivity of informal-skill production and the direct return from the increase in the action-oriented trait. By assumption, productivity $b(J)$ is increasing in the action-oriented trait, so this term is positive. The second term is the indirect effect: the change in earnings due to changes in the optimal time allocation s^*. As shown earlier, an increase in the action-oriented trait leads to an increase in the time investment (Δs). This reallocation results in a shift from formal skills to informal skills. However, at the optimum, as shown in Expression 5, the productivity of informal skills must be lower than the productivity of formal skills. Taken together, the indirect effect is negative.

Intuitively, students with a lower initial comparative advantage in socializing (low action-oriented trait in relative terms) take a larger hit from investing more in s, because their comparative advantage is in formal skills (or educational capital), from which they are substituting away by increasing s. At the same time, $\partial s^*(N,J)/\partial J$ is smaller for students with a comparative advantage in studying.

In total, the sign of Expression 11 is ambiguous. If the gains from the direct effect are larger than the losses from the indirect effect, we should expect a positive return to the action-oriented trait conditional on the school-oriented trait.

4 Results

4.1 Personality and Academic Performance

This section establishes the empirical relationship between academic achievement and our personality measures and uses the results to create a simple 'trait taxonomy' for subsequent analysis. We estimate:

$$H_{it} = P_i'\beta + \delta_t + \epsilon_{it} \tag{12}$$

where H_{it} is a test score measuring academic performance and P_i is a vector of personality traits for person i in birth cohort t.

Table 1 shows the OLS regression results, where the eight personality traits are used as linear predictors for the high-school test scores. Each test score and personality trait is normalized within the analyzed sample. The first four columns represent different high-school subjects as outcome variables. A clear pattern emerges from the partial correlations: sociability, activity-energy, and masculinity consistently negatively predict academic test scores, while deliberation, dutifulness, achievement-striving, and leadership motivation positively predict higher test scores.[12] The relative impact varies somewhat by subject, but confidence and achievement-striving are the strongest positive predictors, whereas sociability is the strongest negative predictor, with the exception of the verbal test, where all three negative traits have roughly equal importance. Overall, personality traits explain 9-13% of the variation in high-school test scores.

The pattern holds for a wide set of educational outcomes. Columns 5-7 show that it holds for 9th grade GPA, selection into high school, and years of schooling. At every level, individuals with high sociability, activity-energy, and masculinity place lower in the intensive margin (grades/test scores) as well as in the extensive margin (selection into education).

Next, we use the dichotomy of positive and negative traits to reduce individual personality into just two distinct dimensions: an index that predicts positive test-score performance and an index that predicts negative test-score performance. For each individual, each index takes a value that is the weighted average of the corresponding traits. Column 4 of Table 1 shows the weights from the anchoring regression, where the overall test score average is used as the response variable. While the choice of the response variable is somewhat arbitrary, our analysis is robust to using any specific test score as the response variable.[13] For the rest of the paper, based on their intuitive appeal, we

[12] In a misspecified model, this pattern could arise incidentally in the presence of multicollinearity between personality traits. Table 6 in Appendix C shows a full cross-correlation table that demonstrates the same pattern with pairwise correlations.

[13] An alternative weighting scheme is to use component scores from principal component analysis

call the index of positive traits 'school-oriented' and the inverse of the index of negative traits 'action-oriented'. Note that 'positive' and 'negative' are used only to describe their association with educational outcomes. We do not imply that action-oriented traits in this context are negative in any other sense.

Our model provides a framework to understand these results. In the model, some personality traits make social activities more attractive at the expense of studying, and vice versa. This causes students highly endowed on those traits to allocate their time differently, resulting in the inverse bundling of those traits with school performance. The strength of the inverse relationship between school test scores and personality traits depends on the joint distribution of personality traits (N and J in our model) and the impact of personality on the utility of socializing (V) and the productivity of socializing and studying (functions a and b).

In subsequent analysis, we apply a similar anchoring procedure to compare the test scores of the two different tracks of mathematics, basic and advanced. A single mathematics test score for each individual is obtained by regressing the military mathematics test results (available for everyone in the sample) on the test scores from the two high-school mathematics tracks and using the coefficients to weight the test scores. Appendix A outlines the details of this procedure.

4.1.1 Why not Use Factor Analysis and the Big Five Model?

The usual approach to dimension reduction with multidimensional data follows the principles of Exploratory Factor Analysis (EFA). The idea is to group closely correlated variables into a single variable—the latent factor. Jokela et al. (2017) and Izadi & Tuhkuri (2021) conduct EFA using the psychological traits in the Finnish Defence Force data. Izadi & Tuhkuri (2021) show that reducing the eight personality traits into two factors results in a very different grouping in comparison to the indices used in this paper. Specifically, in EFA, dutifulness and deliberation mostly load onto one factor, and sociability, activity-energy, leadership motivation, and self-confidence load onto the other [14]. This division is broadly consistent with the Big Five model of personality. In the literature, each of the Big-Five domains can be further divided into 'facets', or subgroups of traits. Deliberation and dutifulness are facets associated with conscientiousness whereas, sociability, activity-Energy and self-Confidence are facets associated with extraversion.

Importantly, the patterns we find in this paper do not emerge by replacing the school-oriented and action-oriented index by the two factors found with EFA. The rea-

(separately applied to negative/positive traits). The indices obtained in this manner have a 0.99 correlation with indices obtained from our preferred anchoring method.

[14] Achievement motivation loads onto both but masculinity does not load strongly onto either.

son is that, for example, the factor associated with extraversion assigns positive loadings to both, traits that predict academic success (self-confidence, leadership motivation, achievement motivations), and traits that predict bad academic performance (sociability and activity-energy). In other words, the top level Big Five categorization is too coarse and does not capture the nuanced effects of individual facets/traits adequately for our purpose. The inadequacy of the Big Five domains in predicting behaviors is not itself a new finding (Paunonen & Ashton, 2001; Vainik et al., 2019), but it warrants a method of dimension reduction that is specifically tailored for the behavior that we study: educational attainment. With this in mind, we purposefully group the traits based on their relation to educational attainment, even when they belong to different Big Five domains. The indices that arise from this exercise should not be viewed as factors since they are not constructed based on the cross-correlation of individual items with each other, as in factor analysis, but rather on their correlation with a common outcome: educational attainment. For example, masculinity (which is a non-standard item in personality questionnaires), is not strongly correlated with any other trait, but is included in our action-oriented index as a strong predictor of bad school performance. As such, our composite indices are most closely related to the economic concept of 'types', which relate parameters directly to behaviors. This is also reflected in our model. Our approach is in the spirit of recent discussions in personality psychology that emphasise the importance of the narrower facets over the broader domains to explain the causal mechanisms of personality on outcomes (see Mõttus 2016).

4.2 Personality and Labor-Market Performance

We estimate an earnings regression where the logarithmic prime-age earnings (Y) are regressed on the intensity of action-oriented (J) and school-oriented (N) traits, and in some specifications also on IQ and high-school test scores (H):

$$Y_{it} = \beta_1 N_i + \beta_2 J_i + H_i' \beta + \delta_t + \epsilon_{it} \tag{13}$$

where i indexes individuals and t indexes birth cohorts. The construction of the school-oriented and action-oriented trait-indices is described in the previous section. The test-score vector H can include test scores from mathematics, verbal, and elective subjects. Birth-cohort fixed effects δ_t are always included to facilitate pooled cross-sectional analysis. Earnings are calculated from the tax register as the sum of inflation-adjusted labor and entrepreneurial income averaged over age 35-38. An age interval is used to reduce measurement error and eliminate zeroes. The upper bound is chosen so that tax records exist for the last cohort (1979) in the last year of our main sample (2017).

Our main analysis sample includes male high-school graduates born in 1962-1979 for whom we have military test records. In the baseline estimation, all predictors are normalized to have zero mean and unit standard deviation within birth cohorts. High-school test scores are from a nationwide high-school exit exam taken around age 18. The military test is standardized also across cohorts and completed shortly after high school during basic training. All tests are graded in a double-blind procedure.

Table 2 presents the estimates of the β coefficients at different stages of saturation.[15] Column 1 shows that action-oriented and school-oriented traits have independent predictive power on earnings. The standardized coefficients of both measures are statistically significant and large in magnitude. The action-oriented trait has a lower earnings premium at 5.3 log points per standard deviation increase in the trait, while the premium for the school-oriented trait is almost twice as large, 9.6 log points.

Column 2 shows the coefficient for high-school mathematics score without controlling for traits. The earnings premium for mathematics is 16.4 log points per one standard deviation increase in the test score. Column 3 estimates the returns to the action-oriented trait, school-oriented trait, and mathematics in the same regression. Compared to column 1, the action-oriented trait's coefficient is almost double and, the school-oriented trait's coefficient is less than half. In contrast, the coefficient for mathematics barely moves.

Column 4 displays the estimates with additional high-school test score measures and IQ. The results reinforce the pattern observed in Column 3: The action-oriented trait coefficient further increases, and the coefficients for the school-oriented trait and mathematics decrease. The results imply that conditional on a comprehensive battery of standardized measurements around age 18, men who rank one standard deviation above the mean in the action-oriented trait earn over 11 log points more relative to the mean ranked men. This is comparable to men who score one standard deviation higher in the mathematics test and earn a 13 log point earnings premium. In this specification, only the test scores for elective subjects hold any non-negligible predictive power over mathematics scores and the action-oriented trait. For simplicity, in further analysis, we compare results from specifications 1 and 3.

In view of our model, estimates from Column 1 correspond to the marginal returns of the endowments (Expression 11). Conditional on the school-oriented trait, the returns to the action-oriented trait comprises of two opposite effects: the positive direct effect of having higher informal skills and the negative indirect effect due to decreased study effort. The positive sign of the action-oriented trait implies that the direct effect, on average, dominates the indirect effect. The results are also consistent with the prediction

[15] In Appendix C, Table 9 shows the results when the school-oriented and action-oriented indices are replaced with the original personality measures. Table 10 shows that the observed patterns are robust to using levels of earnings. Table 11 shows that the results are not sensitive to truncating the long left tail in the log earnings distribution.

that the marginal returns to the school-oriented trait are always positive.

Empirically, the behavior of the action-oriented and school-oriented coefficients is best understood in the light of the results from Section 4.1. If academic performance is rewarded in the labor market, the school-oriented trait should have a positive premium in a regression without test score controls, because school-orientation is positively correlated with test-score performance. Additionally, school-oriented traits could improve earnings more directly if, for example, they foster noncognitive skills that are not particularly useful in studying but still improve job performance in some tasks. We do not find that the school-oriented trait is independently valued in the labor market, as evidenced by the small coefficient in the baseline specification. This is in contrast with studies that look at the correlation of personality traits with earnings without taking into account school performance (Almlund et al., 2011).

Our model abstracts from unobserved heterogeneity in students' preferences. However, an unobserved component is necessary to make sense of estimating traits and test scores in the same regression—otherwise there would be no variation in test scores conditional on traits. If the unobserved tastes are uncorrelated with ϵ_i (conditional on N and J), then the coefficient of mathematics corresponds to the returns r_H in our model. The coefficient of J, on the other hand, could be interpreted as the direct effect in Expression 11. The indirect effect is zero, because controlling for test scores holds socializing constant ($\partial s^*(N, J)/\partial J = 0$).

Note that while there is a mechanical aspect to the shrinking of the school-oriented trait due to its definition, is not mechanically driven to zero if there were to exist a direct channel of influence ($r_N > 0$). Additionally, IQ behaves in a very similar way to the school-oriented trait in the regressions. One interpretation is that the labor market rewards IQ and school-orientation because it enables success in tasks similar to test performance.

The two different estimates for the action-oriented trait can be understood in terms of timing. The estimate in Column 1 represents the effect of having a different endowment at the beginning of schooling. The estimate in Column 3, on the other hand, represents what the returns to informal skills would be if informal skills could be altered independently of educational capital, for example, after already completing education.

4.2.1 Returns to Skills within Occupations and Education

Why is the worse predictor of school performance such a strong predictor of earnings? In this section, we discuss the potential mechanisms that give rise to these premiums. We analyze selection into different education paths and occupations, and experience, career advancement, and job performance within occupations.

Table 3 presents results from the baseline regression (13) where fixed effects are progressively added for the level of education, occupation, and firm.[16] In column 2, the inclusion of occupation and education fixed effects shrinks the coefficient of school-oriented from 0.096 to 0.013, over an 85% decrease. Conversely, the coefficient of the action-oriented trait is almost unchanged from 0.53 to 0.51. This suggests that a large part of the premium for the personality that predicts school performance arises from sorting into profitable education paths and higher-paying occupations. In contrast, the premium for the action-oriented trait is less affected by sorting.

Are action-oriented men able to sort into higher-paying firms within the same occupation? Column 6 adds a firm fixed effect in addition to occupation and education fixed effects. This regression already explains 58% of the variation in adult earnings. While reducing the action-oriented trait's coefficient, its premium is still economically significant and almost twice as large as the coefficient for mathematics. The results imply that action-oriented (one standard deviation above the mean) employees earn 3.5 log points more relative to their colleagues with the same occupational and educational background even within the same firm.

Two caveats relate to these regressions. First, due to selection, labor market outcomes such as firm, education, and occupation are fundamentally 'bad controls' in an earnings regression. For example, Column 6 implies a comparison between men with average action-oriented trait and men with a high action-oriented trait, who are highly educated and working in a high paying occupation. There are likely to be unobservable reasons why these two different types of men would end up in a similar job and education. If the same unobservables influence earnings, it would bias the estimate for the returns to the action-oriented trait *even* if the action-oriented trait was a randomly assigned endowment. However, we find it warranted to draw attention to these suggestive results.

Second, the resolution of the fixed-effect variables matters for the size of the coefficients. Comparing within ever smaller groups almost necessarily decreases the coefficients by accounting for unobservable dissimilarities across larger groups. For this reason, we focus the attention to the relative magnitudes between the action-oriented and the school-oriented traits.

In summary, educational and occupational sorting appear to play an important role in the channel through which personality and academic achievement influence earnings. However, while still considerable, their role appears to be less important for determining the returns to the 'action-oriented' trait.

[16]Some of these variables are included only for a subset of cohorts. This is reflected in the sample size of the regressions. The resolution of these variables consists of 66 categories for 'level $\times$ field of education' ('master's in humanities') and 80 harmonized occupational categories. The variables are recorded at the age of 35.

4.2.2 Occupational Sorting

In this section, we look at occupational sorting in more detail. For the analysis, we estimate Equation 13 with different response variables. We present results with and without mathematics included. Table 5 presents the results when mathematics is included. Column 8 shows that mathematics score and the action-oriented trait have the opposite impact on years of education. A one standard deviation increase in the mathematics scores predicts a 0.9 increase in years of schooling. Conversely, a one standard deviation increase in the action-oriented traits predicts a -0.3 decrease in years of schooling.

Consistent with higher educational attainment, high mathematics scorers work in professional occupations. Columns 1-6 of Table 5 use occupational indicators as the response variable. One standard deviation increase in the mathematics test score predicts a 13 percentage point increase in the probability of working in a professional occupation at age 35. Conversely, a similar increase in the action-oriented trait predicts a 6 percentage point decrease in the probability of working in a professional occupation.[17] On the other hand, a one standard deviation increases in either the mathematics test score or the action-oriented trait increase the probability of being a manager by 2 percentage points or 20%, taking into account the 10% baseline fraction of managers.[18]

Finally, Column 7 uses the average earnings in the individual's occupation as the response variable. The results show that a one standard deviation increase in mathematics test scores is associated with being employed in an occupation with 12 log points higher earnings. Higher action-oriented traits do not predict working in a high paying occupation. In other words, despite earning more themselves, action-oriented men do not work in particularly high-paying occupations. This is consistent with the results from occupational sorting (Columns 1-6). Unlike the mathematics score, the action-oriented trait shows no clear pattern predicting sorting away from low-skill occupations.

How do men spend their years between high school graduation and age 38? The response variables in Table 6 are cumulative years spent in the given activity from age 18 to 38. Columns in Table 6 represent the exhaustive and mutually exclusive list of principal activities recorded by Statistics Finland yearly for each person. By construction, each row sums to zero. The results indicate that a mathematics test score one standard deviation above the mean is associated with 0.43 years of study, and 0.46 years less nonemployment. Conversely, a one standard deviation increase in the action-oriented trait is associated with 0.48 fewer years of studying, 0.66 more years of work experience, and 0.15 fewer years of nonemployment relative to the average individual.

[17] Relative to the baseline of 42%, these numbers correspond to a 31% increase and a 14% decrease in the likelihood of working in a high-level professional occupation.

[18] Our definition of managers excludes small-business owners who perform employee-type work in the firm, such as, owners of small trucking firms.

In other words, for high mathematics men, the time spent studying is fully offset by reduced nonemployment instead of reduced work experience, whereas for the action-oriented men, the offset for the increase in work experience comes from both less time in nonemployment *and* less studying.

In summary, men with a personality that predicts low school performance start their careers earlier, accumulate more work experience by avoiding nonemployment and skipping education, and are more likely to end up in managerial positions relative to their more average peers. They enjoy an earnings premium even without placing in particularly high-paying occupations. Conversely, school achievers manage to educate themselves without compromising work experience. Relative to the average high school graduate, they are more likely to be employed in high-paying professional and managerial occupations. Together, we interpret this as suggestive evidence that action-oriented traits help workers by improving the gradient of their career progress. In contrast, school-oriented traits and mathematics ability help workers to start higher up on the ladder.

4.3 Time Trends in Skill Premiums and Skill Specialization

In the cross-sectional analysis, we show that both the school-oriented and action-oriented traits have considerable earnings premiums. Figure 3 shows how these premiums have changed over time by estimating Equation 13 for each birth cohort separately (omitting the cohort fixed effect). The results show a striking reversal in the magnitude of the premiums over the 16-year period. The premium for the action-oriented trait has increased from virtually zero to almost 9 percentage points per standard deviation. The school-oriented trait has decreased from 0.13 to 0.8 over the same period. Appendix C Figure 7 shows the corresponding figure with mathematics included in the regression.

Our result is consistent with Deming (2017) who finds an increase in the returns to a proxy of sociability between the NLSY79 and NLSY97 cohorts and with Edin et al. (2021) who find an increase in the returns to noncognitive skills in Sweden. However, we show that noncognitive skills are inadequately described by a single dimension, as demonstrated by the opposite trends in the returns to the action-oriented and school-oriented traits. Furthermore, the action-oriented trait appears to measure more than just teamwork-based skills as in Deming (2017). We observe that the increasing trend for the action-oriented trait returns is driven by all three of its components, sociability, activity, and masculinity, not only sociability.[19]

Deming (2017) offers a demand-side explanation of the growing importance of social skills: changing job requirements increase the demand for social skills. Deming shows

[19]Results are available by request.

how the equilibrium employment shares have changed to favor socially intensive jobs at the expense of mathematics-intensive jobs. In the same spirit, but on the supply side, we use tercile cutoffs within cohorts to group men into four bundles: 'school-specialized' (high mathematics, low action-oriented), 'action-specialized' (high action-oriented, low math), both high (high math, high action-oriented) and both low (low math, low action-oriented).

Skill specialization implies inverse bundling of action-oriented personality traits and mathematics skills; we should observe relatively fewer men who rank high in both. Figure 4 shows the evolution of the relative shares of each bundle over time. Each cohort is divided into mutually exclusive groups (bundles) along the tercile cutoffs in their mathematics score and action-oriented trait. Each line represents the evolution of the size of the bundle. Figure 4 shows clearly that skill specialization has increased over time. The largest divergence happens in the latter half of the period (individuals for which labor-market earnings are measured after 2005). Before that, the relative proportions of the bundles are roughly equal. In the last cohort, there are 5 percentage points more inverse bundles (action-specialized and school-specialized) relative to the 'pooling' bundles. From the baseline of 11% share each, this corresponds to 10% increase in the inverse bundles and a 10% decrease in the pooling bundles.

What is driving the increasing separation of school performance and action-oriented traits? If specialization is an equilibrating reaction from the supply side to the increased demand for social skills in the labor market, all students should increase their informal-skill investment. However, students with higher marginal benefits should do so relatively more. In our model, if the marginal cost of studying is increasing in the comparative advantage to the action-oriented trait, we should see the largest time-reallocation towards informal skills for those who already have a comparative advantage in action-oriented traits. Likewise, earnings gains should be largest for 'action-specialized' and smallest for 'school-specialized.' Earnings gains for the separating bundles should fall somewhere in between.

Figure 5 shows the evolution of earnings for each group relative to the cohort born in 1963.[20] Changes in earnings have been uneven across the bundles. Those with high 'action-oriented' traits and low mathematics skills ('action-specialized') had a 20% increase earnings. The earnings of 'school-specialized' improved by less than 10% in the same period. The changes in earnings of high-math/high-action-oriented individuals and low-math/low-action-oriented individuals place between the inverse bundles.

In summary, our results are consistent with a supply-side response to the increased returns of social skills. Simultaneously, we emphasize that while the novel descriptive trends are robust, a full explanation for the trends requires further research.

[20]We omit the 1962 cohort because it has substantially fewer observations.

4.4 The Reading Penalty

This section relates our results to the 'reading penalty' feature found in several US longitudinal data sets. Sanders (2015) and Altonji et al. (2016) show that in a wage regression that includes both mathematics and verbal test scores as regressors, the verbal score has a negative coefficient. Sanders (2015) demonstrates that this is a robust feature of five commonly used US longitudinal data sets.[21] That study controls for occupational and educational sorting and crude measures of personality but still finds a negative partial correlation between the verbal test scores and wages.

Column 1 of Table 7 shows the results of estimating Equation 13 in our data with only high-school test scores as regressors. We also find a small negative coefficient of -0.6 log points for the verbal test. Similarly, controlling for education and occupation in Columns 2 and 3 only serve to reduce the math and electives coefficients, but not the one for verbal scores. We also conclude that differential occupational sorting is not the source of the reading penalty.

Column 4 adds personality and IQ controls to the regression. In this specification, verbal scores have a slightly positive coefficient of 0.5 log points. While not conclusive, the evidence supports the hypothesis that inverse bundling of personality and verbal skills contributes to the observed reading penalty, and that the returns to verbal skills in the labor market are low. In view of our framework, action-oriented students invest less in verbal skills. If the returns to verbal skills are particularly low, the only ones investing in them are students who have a high comparative advantage in the school-oriented trait.[22]

5 Conclusion

This paper analyzes how do different dimensions of personality predict school vs. labor-market performance, and how the labor-market value of these traits has changed over time. It uses data that includes multidimensional personality and cognitive ability measures, education, and labor-market records for 79% of Finnish men.

We demonstrate that to understand the role of noncognitive skills in the labor market it is essential to consider the multidimensional nature of skills. The key reason is that different dimensions of noncognitive skills appear to have opposite effects in human capital production relative to the labor market. At its core, the paper considers the distinction between the school versus the labor-market. We find that high achievers in school lack, on average, at least in some dimensions of economically valuable personality

[21] NLSY79, NLSY97, NELS88, ELS88 and Baccalaureate and Beyond (Sanders, 2015)

[22] In an extension to our framework, productivity for mathematics and verbal skills could depend on different kinds of traits which we measure imperfectly.

traits. Conversely, low-achieving students tend to have some redeeming qualities that compensate in the labor market for their lack of academic success.

We formalize this idea using a model of multidimensional skill specialization. Variation in initial personality endowments generates differences in comparative advantage that leads to specialization in 'school-orientation' and 'action-orientation.' We explore the empirical implications of this model on educational and occupational sorting and careers. Using the model to structure our analysis, we provide four new empirical facts.

First, a particular subset of personality traits predicts high educational achievement, but another critical subset of personality traits predicts low achievement. This pattern follows the common stereotypes: men, who score high in sociability, activity-energy, and masculinity, tend to perform worse in standardized school tests. Achievement striving, dutifulness, and deliberation predict good school performance.

Second, the traits that predict low school achievement still predict labor market success. Conditional on test scores, one standard deviation increase in these traits predicts a 10 log point increase in earnings at age 35. The corresponding returns to mathematics in the same regression is 16 log points. In contrast, the traits that predict higher school achievement are not independently valued in the labor market.

Third, the economic returns to traits that predict low school performance have rapidly increased over the past two decades. Men with high sociability, activity-energy, and masculinity, but with low math skills, experienced the highest earnings gains. Returns to traits that predict high school achievement have declined, and cognitive skills returns have been stable.

Fourth, skill specialization has increased over the past two decades: men have become more likely to possess either good formal or informal skills and are less likely to have both.

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Tables

Table 1: Personality and Academic Performance

	High School Test Scores						
	Math	Verbal	Electives	HS GPA	In HS sample	9th grade GPA	Years of Education
Sociability	−0.258	−0.162	−0.219	−0.220	−0.054	−0.202	−0.335
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)	(0.006)
Activity	−0.122	−0.189	−0.145	−0.215	−0.099	−0.186	−0.448
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)	(0.005)
Masculinity	−0.032	−0.147	−0.126	−0.161	−0.059	−0.134	−0.222
	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)
Deliberation	0.113	0.081	0.102	0.085	0.005	0.055	0.197
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)
Dutifulness	0.011	0.083	0.068	0.064	0.059	0.164	0.232
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)	(0.005)
Achievement Aim	0.190	0.168	0.198	0.224	0.111	0.301	0.636
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.003)	(0.005)
Confidence	0.263	0.151	0.181	0.219	0.097	0.249	0.508
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)	(0.005)
Leadership	0.070	0.111	0.142	0.121	0.081	0.091	0.257
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.005)	(0.006)
Y mean	0.000	0.000	0.000	0.000	0.360	0.000	12.890
Cohort FE	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.090	0.095	0.111	0.128	0.206	0.249	0.190
Observations	157129	157129	150610	162605	459357	119902	457529

Notes: Each column reports the OLS regression results from Equation 12. The column name indicates the outcome. The unit of observation is the person. The standardized high school (HS) tests are administered by the Matriculation Examination Board before military service. Personality traits are measured by the Finnish Defence Force after high school. Test scores and personality traits are normalized to have mean 0 and standard deviation 1 within cohorts. All models control for the birth year (cohort) fixed effects. Robust standard errors are reported in parentheses.

Table 2: Returns to Skills

	Dependent variable: log earnings			
	(1)	(2)	(3)	(4)
Action-oriented	0.053		0.099	0.112
	(0.003)		(0.003)	(0.003)
School-oriented	0.096		0.036	0.018
	(0.003)		(0.003)	(0.003)
Math		0.164	0.160	0.130
		(0.002)	(0.002)	(0.002)
IQ				0.012
				(0.002)
Verbal				0.005
				(0.002)
Electives				0.052
				(0.002)
Outcome mean	10.520	10.520	10.520	10.520
Cohort FE	yes	yes	yes	yes
Adj. R^2	0.048	0.063	0.093	0.098
Observations	157743	157891	157129	156843

Notes: Each column reports the OLS regression results from Equation 13, with log earnings as the outcome. The unit of observation is the person. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 3: Returns to Skills within Occupation and Education

	Baseline			With math control		
	(1)	(2)	(3)	(4)	(5)	(6)
Action-oriented	0.086	0.051	0.035	0.097	0.057	0.040
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
School-oriented	0.022	0.013	0.011	0.009	0.006	0.007
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Math				0.066	0.035	0.028
				(0.002)	(0.002)	(0.002)
Outcome mean	10.520	10.520	10.790	10.520	10.520	10.790
Cohort FE	yes	yes	yes	yes	yes	yes
Education FE	yes	yes	yes	yes	yes	yes
Occupation FE	no	yes	yes	no	yes	yes
Firm FE	no	no	yes	no	no	yes
Adj. R^2	0.171	0.328	0.575	0.177	0.331	0.577
Num. obs.	157743	100472	61224	157129	100003	60940

Notes: Each column reports the OLS regression results from Equation 13, with log earnings as the outcome. All models control for the birth year (cohort) and additional fixed effects as indicated. Sample size varies when variables are available only for a subset of cohorts. When firm FE is included, public sector employees are excluded. The unit of observation is the person. The standardized high school (HS) tests are administered by the Matriculation Examination Board before military service. Personality traits are measured by the Finnish Defence Force after high school. The action-oriented trait is a composite of Sociability, Activity, and Masculinity. The school-oriented trait is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 4: Occupational Sorting

	Occupations							
	Managers	Professionals	Technical/Clerical	Service/Sales	Production	Other	Mean Earnings	Years of Educ.
Action-oriented	0.014	−0.099	0.027	0.018	0.035	0.005	−0.030	−0.796
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
School-oriented	0.027	0.111	−0.038	−0.019	−0.066	−0.016	0.088	1.443
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
Outcome mean	0.100	0.420	0.290	0.060	0.100	0.030	10.680	12.890
Cohort FE	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.024	0.028	0.004	0.009	0.028	0.006	0.062	0.188
Observations	100472	100472	100472	100472	100472	100472	80186	457529

Notes: Each column reports the OLS regression results from Equation 13.The column name indicates the outcome. Each outcome variable is an indicator of working in the given occupation at age 35 (at the end of the calendar year). The outcome in the last column measures the average earnings of all other men employed in the same occupation at age 35. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 5: Occupational Sorting with Math

	Occupations							
	Managers	Professionals	Technical/Clerical	Service/Sales	Production	Other	Mean Earnings	Years of Educ.
Action-oriented	0.020	−0.060	0.011	0.006	0.021	0.002	0.007	−0.297
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
School-oriented	0.019	0.063	−0.018	−0.003	−0.049	−0.012	0.043	0.568
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Math	0.022	0.129	−0.053	−0.042	−0.046	−0.010	0.120	0.929
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)
Outcome mean	0.100	0.420	0.290	0.060	0.100	0.030	10.680	14.740
Cohort FE	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.029	0.091	0.016	0.035	0.050	0.009	0.215	0.211
Observations	100003	100003	100003	100003	100003	100003	79804	156016

Notes: Each column reports the OLS regression results from Equation 13.The column name indicates the outcome. Each outcome variable is an indicator of working in the given occupation at age 35 (at the end of the calendar year). The outcome in the last column measures the average earnings of all other men employed in the same occupation at age 35. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 6: Cumulative activity, Ages 18-38

	Baseline				With math control			
	Work Experience	Study	Nonemployment	Other	Work Experience	Study	Nonemployment	Other
Action-oriented	0.647	−0.607	−0.015	−0.024	0.662	−0.477	−0.150	−0.036
	(0.015)	(0.012)	(0.008)	(0.005)	(0.016)	(0.012)	(0.008)	(0.005)
School-oriented	−0.139	0.408	−0.314	0.045	−0.162	0.247	−0.146	0.060
	(0.015)	(0.011)	(0.008)	(0.004)	(0.016)	(0.012)	(0.008)	(0.005)
Math					0.062	0.432	−0.455	−0.038
					(0.011)	(0.008)	(0.006)	(0.003)
Outcome mean	14.360	4.510	1.050	1.080	14.360	4.510	1.050	1.080
Cohort FE	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.039	0.033	0.041	0.021	0.039	0.060	0.103	0.022
Observations	98138	98138	98138	98138	97658	97658	97658	97658

Notes: Each column reports the OLS regression results from Equation 13. The column name indicates the outcome. The outcome variable is measured in years. The unit of observation is the person. The standardized high school (HS) tests are administered by the Matriculation Examination Board before military service. Personality traits are measured by the Finnish Defence Force after high school. The action-oriented trait is a composite of Sociability, Activity, and Masculinity. The school-oriented trait is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. All models control for the birth year (cohort) fixed effects. Robust standard errors are reported in parentheses.

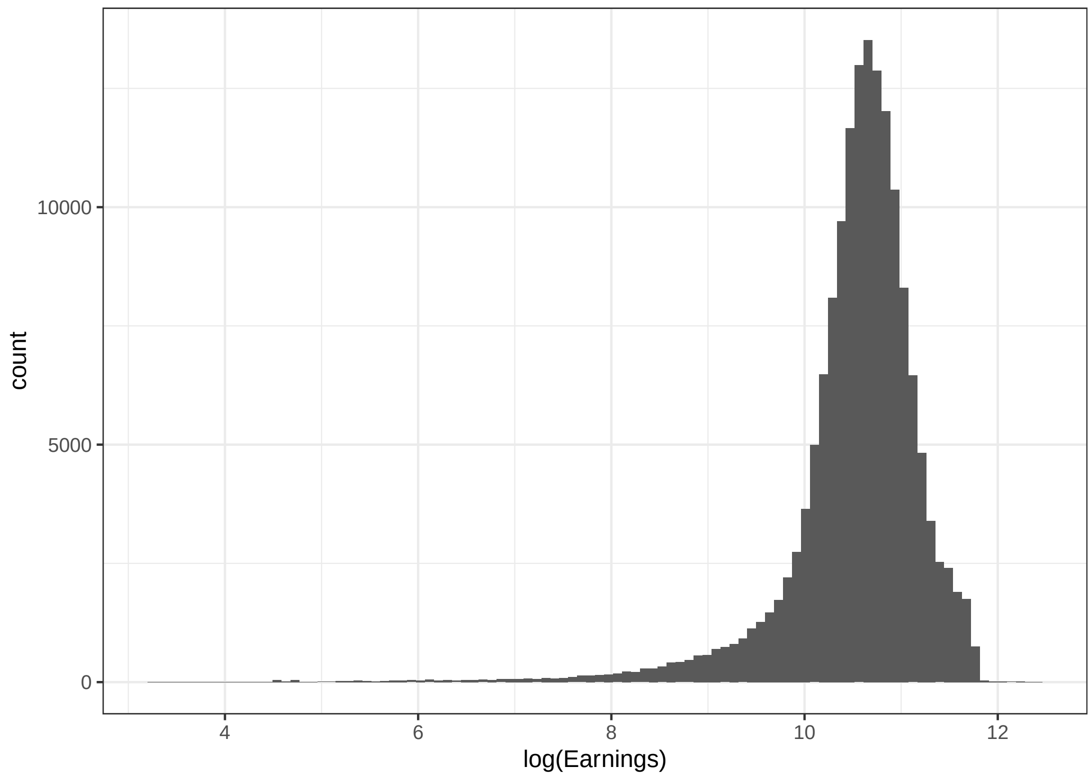
Table 7: Reading Penalty

	Earnings	Earnings	Earnings	Earnings
Math	0.138	0.056	0.027	0.130
	(0.002)	(0.002)	(0.002)	(0.002)
Verbal	−0.006	−0.010	−0.004	0.005
	(0.002)	(0.002)	(0.002)	(0.002)
Electives	0.056	0.024	0.018	0.052
	(0.002)	(0.002)	(0.002)	(0.002)
Action-oriented				0.112
				(0.003)
School-oriented				0.018
				(0.003)
IQ				0.012
				(0.002)
Outcome mean	10.520	10.520	10.520	10.520
Cohort FE	yes	yes	yes	yes
Education FE	no	yes	yes	no
Occupation FE	no	no	yes	no
Adj. R^2	0.068	0.158	0.319	0.098
Observations	157605	157605	100031	156843

Notes: Each column reports the OLS regression results from Equation 13, with log earnings as the outcome. All models control for the birth year (cohort) and additional fixed effects as indicated. The unit of observation is the person. The standardized high school (HS) tests are administered by the Matriculation Examination Board before military service. Personality traits are measured by the Finnish Defence Force after high school. The action-oriented trait is a composite of Sociability, Activity, and Masculinity. The school-oriented trait is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

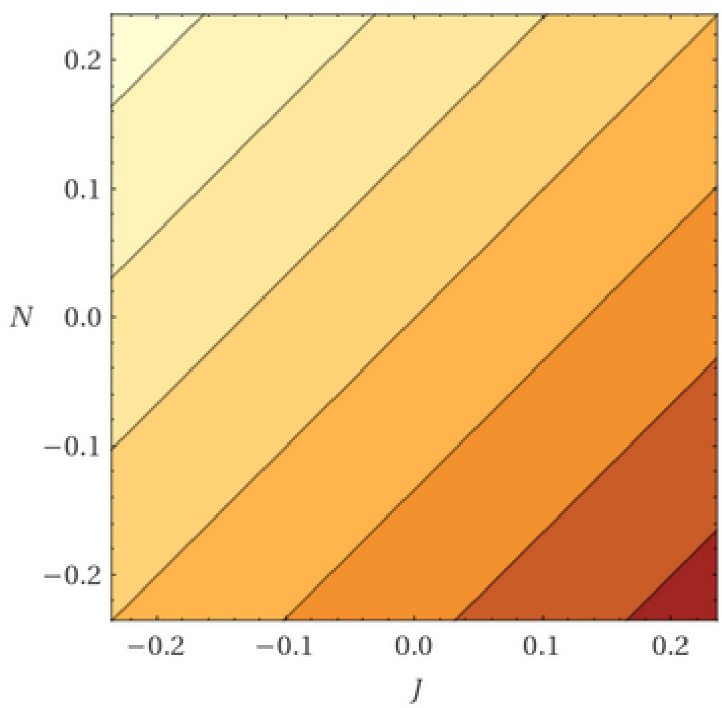
Figures

Figure 1: Distribution of Log Earnings



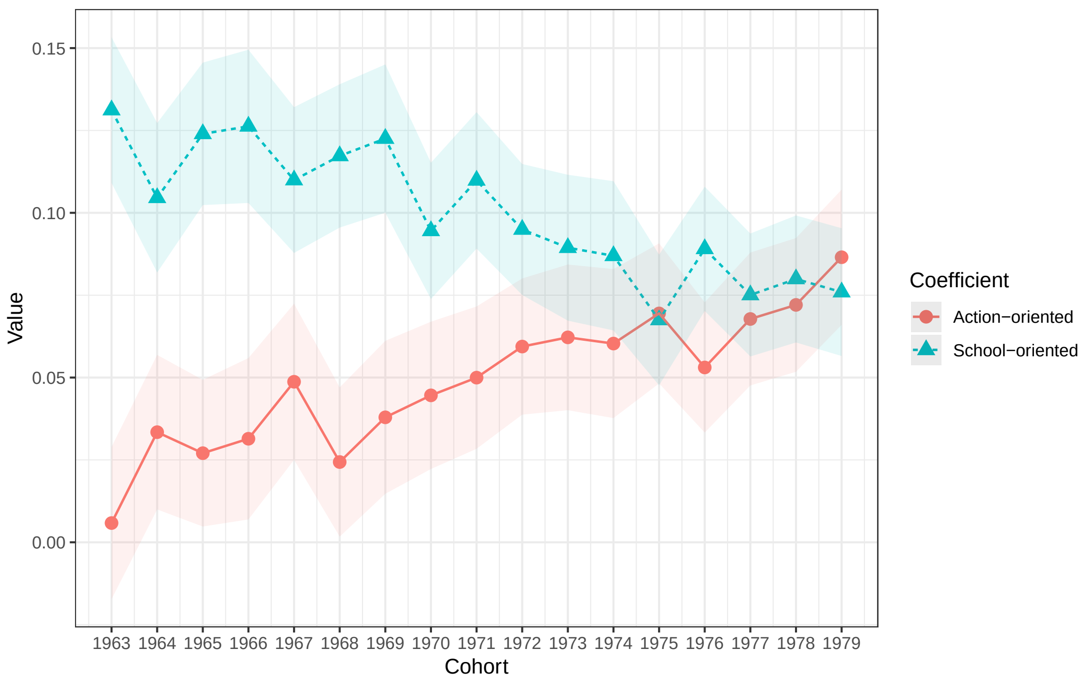
Notes: The histogram shows the distribution of log earnings in the main sample of male high school graduates with military test scores. In the sample, n = 158,000, mean = 10.5, SD = 0.72.

Figure 2: Comparative Advantage



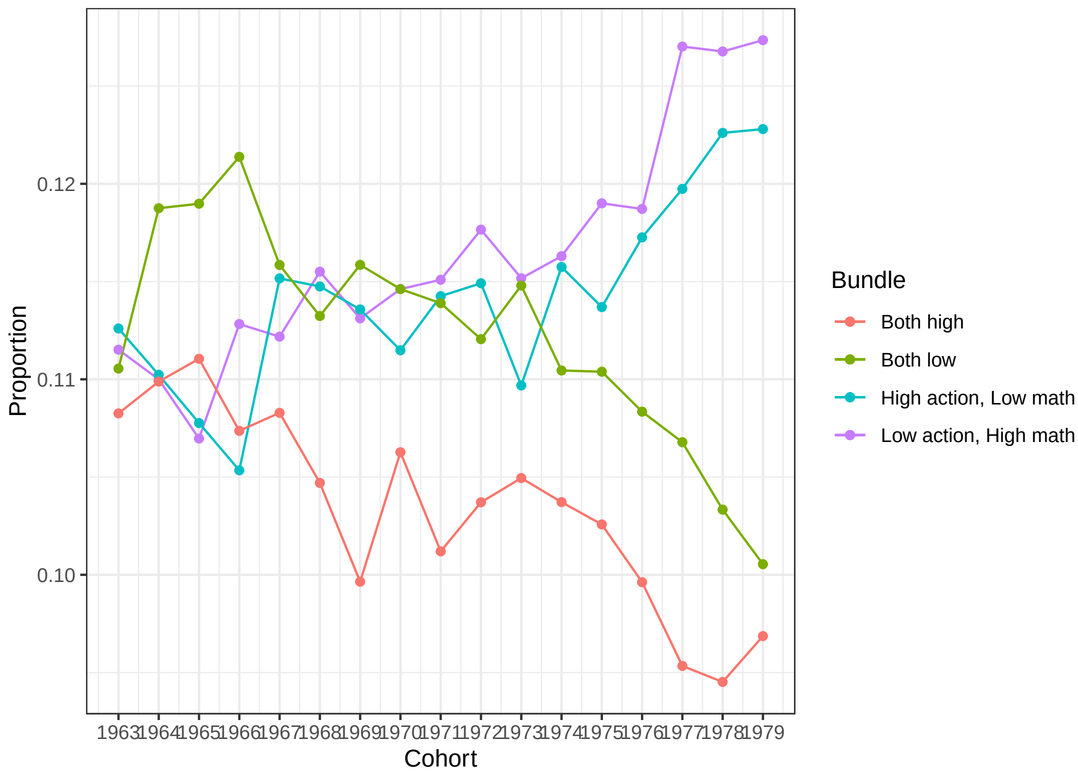
Notes: Each line represents an isoquant in a plane where J and N are in the x and y axis and $s^*(N, J)$ is in the z axis. Darker shades indicate higher values of z. Functional form choices are $a(N, J) = N$, $b(N, J) = J$, $C(1 - s, N, J) = (J + (1 - s))^2$.

Figure 3: Time Trends in Returns to Traits



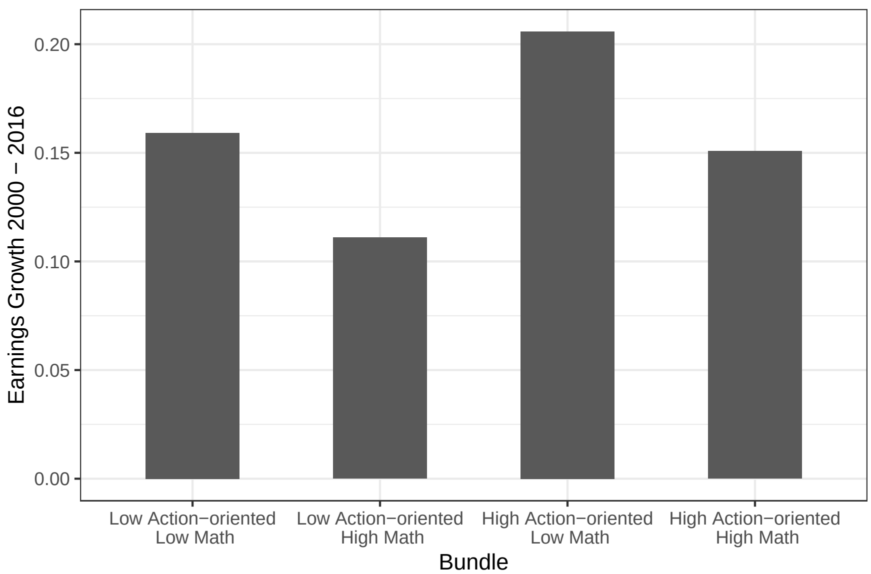
Notes: Each point in the figure corresponds to a regression coefficient from estimating Equation 13 separately for each cohort, with log earnings as the outcome and person as the unit of observation. The right-hand-side variables include only the action-oriented and school-oriented traits. The action-oriented trait is a composite of Sociability, Activity, and Masculinity. The school-oriented trait is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. All covariates are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported as the shaded area.

Figure 4: Time Trends within Bundles



Notes: Each point corresponds to the proportion of persons belonging to the indicated group (bundle) within that cohort. The 'High action, Low math' bundle includes persons who belong to the top tercile in the action-oriented trait and the bottom tercile in the math score. The 'Low action, High math' bundle includes persons who belong to the bottom tercile in the action-oriented trait and the top tercile in the math score. The 'Both high' bundle includes persons who score in the top tercile in both dimensions and vice versa for the 'Both low' bundle.

Figure 5: Earnings Change within Bundles



Notes: Each bars corresponds to the change median earnings of that bundle relative to the base year 1963. The 'High action, Low math' bundle includes persons who belong to the top tercile in the action-oriented trait and the bottom tercile in the math score. The 'Low action, High Math' bundle includes persons who belong to the bottom tercile in the action-oriented trait and the top tercile in the math score. The 'High action, High math' bundle includes persons who score in the top tercile in both dimensions and vice versa for the 'Low action, Low math' bundle.

A Appendix: Data

Part 1. The Finnish Defence Forces (FDF) Test Data

Background Military conscription in Finland is universal and grants relatively few exceptions. The available data cover 80% of Finnish men born between 1962 and 1979 (n = 489,252). Finnish men are drafted in the year they turn 18 and most start their service at age 19 or 20. Military service lasts for 6–12 months, and most conscripts do not continue service at the military.

FDF uses psychological tests as of the criteria to assess conscripts' suitability for non-commissioned officer training. FDF conducted psychological tests on all conscripts since 1955. Between 1955 and 1982, FDF used one test that measured cognitive skills: logical, mathematical and verbal skills. From 1982, the FDF has used two tests: a cognitive and a personality test. The content of each test is described in the sections below.

The test data have been described in Jokela et al. (2017) and validated in FDF's internal reports summarized in Nyman (2007).

Administration of the Tests The cognitive ability test and the personality test are typically taken in the second week of military service in a 2-h paper-and-pencil format in standardized group-administered conditions. The personality test contains 218 statements with a response scale of yes/no. The cognitive test contains 120 multiple-choice questions. The test questionnaires have been unchanged from 1982 to 2000 (the data available to this study), and the scores are designed to be comparable across cohorts. The main change in the test administration during the timeline of this study is that between 1995 and 2000, the personality test was administered already at the conscription, on average 18 months before entering the FDF service. The administration of the cognitive test has been unchanged 1982–2000.

The Cognitive Ability Test The cognitive ability test has three subtests: visuospatial, arithmetic and verbal reasoning. The FDF cognitive ability test is similar to the The Armed Services Vocational Aptitude Battery (ASVAB), administered by the United States Military Entrance Processing Command. Each subtest has 40 multiple-choice questions. FDF reports test–retest reliabilities of the subtests between 0.76 and 0.88 Nyman (2007). The descriptions of tests are based on Nyman (2007) and Jokela et al. (2017):

1. *The visuospatial subtest* is similar to Raven's Progressive Matrices (Raven et al., 2000). The test shows a set of matrices, each with one removed part, and the participant choose a figure that completes the matrix.

2. *The arithmetic subtest* contains different tasks: computing arithmetic operations, completing a series of numbers that follow a pattern, solving short verbal problems, and noticing similarities in relationships between numbers.

3. *The verbal subtest* requires choosing synonyms or antonyms, selecting a word that belongs to the same category as the given pair of words, choosing which word on a list does not belong in the group, and detecting similar relationships between two pairs of words (Jokela et al., 2017).

The Personality Test The personality test aims to measure 8 personality traits. The test is similar to and partly based on the Minnesota Multiphasic Personality Inventory (MMPI). It contains 218 statements with a yes/no response scale—between 18 and 33 items for each personality trait. The test score for each personality trait is the sum of the binary answers aligned with the trait (for example, in reverse-coded statements, cases where the task-taker disagrees). The data available to this study contain these sums of scores. FDF reports that internal reliability varies between 0.6 and 0.9 by trait and that the average Cronbach alpha is 0.75 Nyman (2007).

The 8 personality traits measured in the test are, as described by Jokela et al. (2017):

1. *Sociability*: the person's level of gregariousness and preference for socializing with others (33 items; e.g., whether the person likes to host parties and not withdraw from social events).

2. *Activity–energy*: how much the person exerts physical effort in everyday activities and how quickly the person prefers to execute activities (28 items; e.g., whether the person tends to work fast and vigorously and prefers fast-paced work).

3. *Masculinity*: the person's occupational and recreational interests that are traditionally considered as masculine (27 items; e.g., whether the person would like to work as a construction manager).

4. *Dutifulness*: how closely the person follows social norms and considers them to be important (18 items; e.g., whether the person would return money if given back too much change at a store).

5. *Deliberation*: how much the person prefers to think ahead and plan things before acting (26 items; e.g., whether the person prefers to spend money carefully).

6. *Achievement motivation*: how strongly the person wants to perform well and achieve important life goals (24 items; e.g., whether the person is prepared to make personal sacrifices to achieve success).

7. *Leadership motivation*: how much the person prefers to take charge in groups and influence other people; it includes 30 items.

8. *Self-confidence*: the person's self-esteem and beliefs about his abilities (32 items; e.g., whether the person feels to be as good and able as others and can meet other people's expectations).

Dutifulness, deliberation, achievement striving are all related to the higher order personality factor conscientiousness.

The FDF personality test also includes questions about mental health and questions targeted at evaluating the answers' validity. The mental health part has four mental health sub-scales from the Minnesota Multiphasic Personality Inventory (MMPI), hypochondriasis, psychopathic deviate, psychasthenia, and schizophrenia. The validity part has three sub-scales: lie (attempts to give an overly favorable impression of one's conduct), fix (attempts to give an overly unfavorable impression of one's conduct), and validity (attempts to give unusual, for example, random or contradictory answers).

Selection Concerns The data are subject to two selection concerns. The first concern is selection into military service: Only those that enter the FDF service take the tests. It is possible to be exempted from the military service due to severe health conditions, most often related to mental health problems, or due to religious or ethical convictions. For the analysis, this means that the sample is generally more representative of men with relatively higher labor-market prospects. Over the timeline of this study, selection into military service has been stable Jokela et al. (2017). The second concern is the selective test performance. The military uses the test results for selecting conscripts to officer training. To some extent, this feature is likely to induce higher performance from those that would like to be selected and lower performance that would like to avoid it. For personality data, the concern is alleviated by the fact that the scoring rules are not revealed to the conscripts. For cognitive data, test performance may reflect, to some extent, motivation-related factors, as is the case for most cognitive tests. Finally, the data excludes The Finnish Defense Forces personnel as well as Finnish Border Guard soldiers.

Part 2. Anchoring High-School Test Data

In high school, students can select between two tracks of mathematics; basic and advanced. The exit exams are different for both tracks and a small fraction opts out from both. Our aim is to construct a single measure of mathematics test scores that is commensurable across the three options. We do this by regressing:

$$\begin{aligned}\text{MilitaryMathScore}_{it} = {} & \delta_1 D_i^{\text{BasicMath}} + \delta_2 D_i^{\text{AdvancedMath}} \\ & + \delta_3 D_i^{\text{BasicMath}} \text{BasicMathScore}_i \\ & + \delta_4 D_i^{\text{AdvancedMath}} \text{AdvancedMathScore}_i + \delta_t\end{aligned}$$

where D indicates that person i has participated in the exam. The indicator is interacted with the normalized test score. For those who did not participate, number -1 is imputed for the test score (the scalar used here does not matter for the estimation). Finally, δ_t is a fixed effect for the test-taking year.

The left-hand side variable is the military arithmetic test score. We use the fact that this standardized test is administered to everyone in our data. The military test is low stakes, relatively easy, and only moderately correlated with the high-school test scores (less than 0.4 with either track). While it does not share the same patterns as our main results (results not shown), it is a reasonable tool for this purpose.

Table 8: Math Anchoring Regressions

	Outcome: Military Arithmetic Test
δ_1	0.334
	(0.006)
δ_2	0.810
	(0.005)
δ_3	0.255
	(0.003)
δ_4	0.270
	(0.002)
Num. obs.	165934
Adj. R^2 (full model)	0.269
Adj. R^2 (proj model)	0.255

Notes: Robust standard errors are in parentheses.

Table 8 shows the estimation results. The marginal weights for better test scores are similar in both tracks. Both predict around 0.26 standard deviation increase in the military test for each standard deviation increase in the high school score. The differences arise from a mean shift in the military arithmetic test. The mean performance of students taking the advanced mathematics track is almost 0.5 standard deviations higher than the mean performance of students taking the basic track ($\delta_2 - \delta_1$). The 'math' variable in all results except for Table 1 is the weighted average of the right hand side variables, where the weights are given by the δ values. The cohort fixed effects are not included.

B Appendix: Proofs

Proof. Using equation 5:

$$\begin{aligned}\frac{\partial U(s;N,J)}{\partial s} = -a(N,J) + b(N,J) + \frac{\partial V(s;N,J)}{\partial s} &= 0\\ \frac{\partial C(s;N,J)}{\partial s} &= a(N,J) - b(N,J)\\ s^* &= g_s(a(N,J) - b(N,J); N,J)\end{aligned}$$

■

Comparative static: Optimal response of s to a change in J

Proof. Differentiate with respect to J from both sides of equation 5:

$$\begin{aligned}\frac{\partial^2 V(.)}{\partial s^2}\frac{\partial s^*}{\partial J} + \frac{\partial^2 V(.)}{\partial s^* \partial J} &= a^J(N,J) - b^J(N,J)\\ -\frac{\partial^2 V(.)}{\partial s^2}\frac{\partial s^*}{\partial J} &= b^J(N,J) + \frac{\partial^2 V(.)}{\partial s^* \partial J} - a^J(N,J)\\ \frac{\partial s^*}{\partial J} &= -\left[\frac{\partial^2 V(.)}{\partial s^2}\right]^{-1}\left[b^J(N,J) + \frac{\partial^2 V(.)}{\partial s^* \partial J} - a^J(N,J)\right]\end{aligned}$$

■

Comparative static: Marginal returns to a change in J

Proof. Earnings are given by

$$\begin{aligned}Y &= r_H H(1-s;N,J) + r_S S(s;N,J) + r_N N + r_J J\\ &= r_H a(N,J)(1 - s^*(N,J)) + r_S b(N,J) s^*(N,J) + r_N N + r_J J\\ &= r_H a(N) - r_H a(N) s^*(N,J) + r_S b(J) s^*(N,J) + r_N N + r_J J\end{aligned}$$

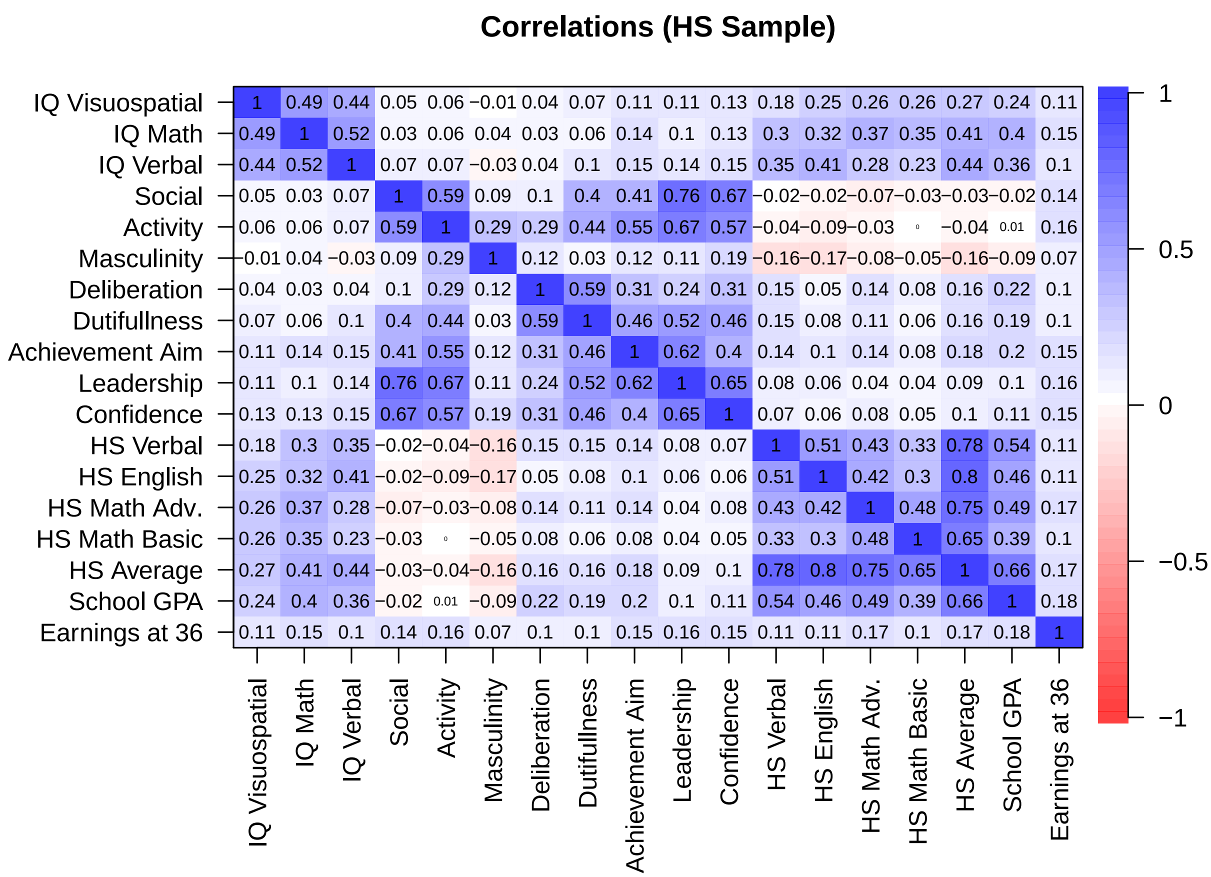
Differentiate with respect to J:

$$\begin{aligned}\frac{\partial Y}{\partial J} =& - r_H a(N)\frac{\partial s^*(N,J)}{\partial J}\\ &+ r_S\left[b'(J)s^*(N,J) + b(J)\frac{\partial s^*(N,J)}{\partial J}\right] + r_J\\ &= \underbrace{r_S b'(J) s^*(N,J) + r_J}_{\text{direct effect}} + \underbrace{(r_S b(J) - r_H a(N))}_{\text{net earnings change}}\underbrace{\frac{\partial s^*(N,J)}{\partial J}}_{\text{change in } s}\end{aligned}$$

■

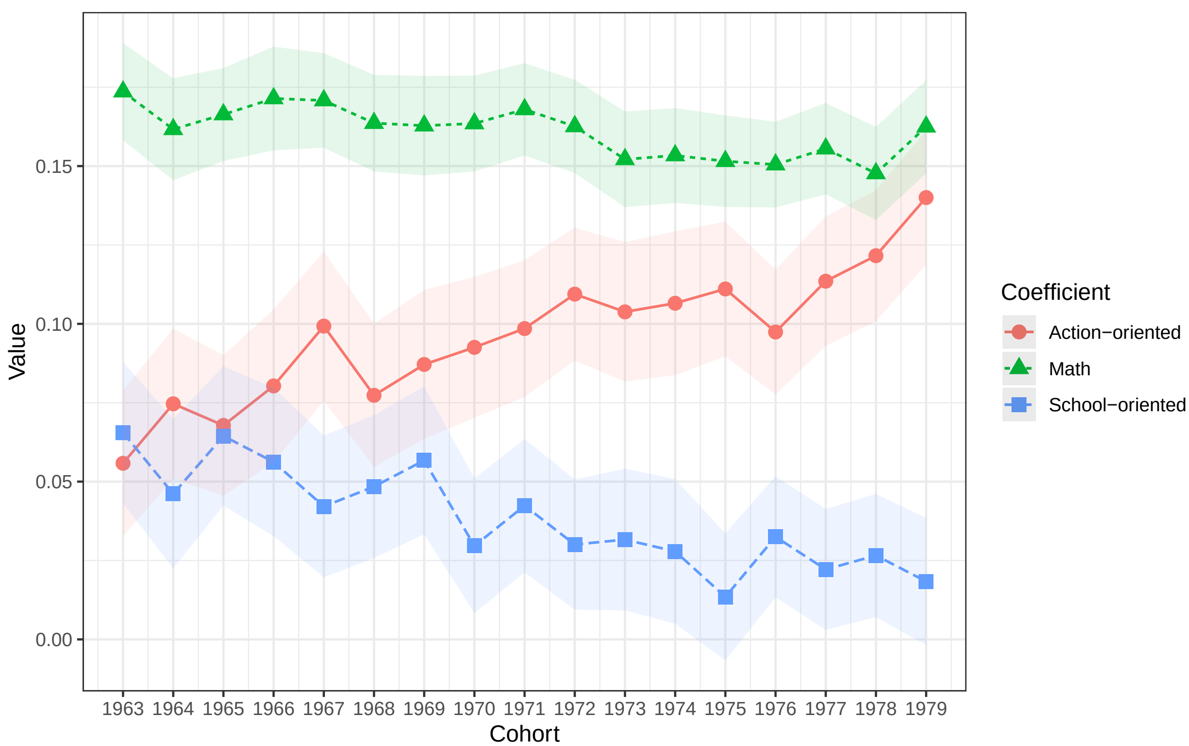
C Appendix: Robustness

Figure 6: Cross-correlations



Notes: Each number is a pairwise correlation coefficient with person as the unit of observation. All variables are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. The data includes only persons for which we have high-school data.

Figure 7: Trends in Trait Premia with Math



Notes: Each point in the figure corresponds to a regression coefficient from estimating Equation 13 separately for each cohort, with log earnings as the outcome and person as the unit of observation. The right-hand-side variables include only the action-oriented and school-oriented traits. The action-oriented trait is a composite of Sociability, Activity, and Masculinity. The school-oriented trait is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. All covariates are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported as the shaded area.

Table 9: Returns to Skills

	Dependent variable: log earnings		
	(1)	(2)	(2)
Sociability	0.019		0.065
	(0.003)		(0.003)
Activity	0.023		0.047
	(0.003)		(0.003)
Masculinity	0.023		0.035
	(0.002)		(0.002)
Deliberation	0.041		0.021
	(0.002)		(0.002)
Dutifulness	−0.032		−0.037
	(0.003)		(0.003)
Achievement aim	0.050		0.017
	(0.002)		(0.002)
Confidence	0.037		0.000
	(0.003)		(0.003)
Leadership	0.038		0.021
	(0.003)		(0.003)
Math		0.138	0.135
		(0.002)	(0.002)
Verbal		−0.006	0.005
		(0.002)	(0.002)
Electives		0.056	0.052
		(0.002)	(0.002)
Outcome mean	10.520	10.520	10.520
Cohort FE	yes	yes	yes
Adj. R^2	0.050	0.068	0.099
Observations	157743	157605	156843

Notes: Each column reports the OLS regression results from Equation 13, with log earnings as the outcome. The unit of observation is the person. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 10: Returns to Skills - Levels

	Dependent variable: Earnings (2010 euros)			
	(1)	(2)	(3)	(4)
Action-oriented	1051.077		2939.034	3678.742
	(77.473)		(76.447)	(78.739)
School-oriented	4816.418		2367.299	1461.602
	(77.647)		(76.984)	(79.139)
Math		6829.824	6480.433	5102.159
		(55.925)	(56.176)	(66.391)
IQ				52.229
				(58.347)
Verbal				690.042
				(63.882)
Electives				2539.078
				(73.595)
Outcome mean	44325	44290	44328	44350
Cohort FE	yes	yes	yes	yes
Adj. R^2	0.076	0.105	0.150	0.160
Observations	157743	157891	157129	156843

Notes: Each column reports the OLS regression results from Equation 13, with earnings in 2010 euros as the outcome. The unit of observation is the person. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.

Table 11: Returns to Skills - Truncated Sample

	Dependent variable: log(Earnings)			
	(1)	(2)	(3)	(4)
Action-oriented	0.034		0.078	0.092
	(0.002)		(0.002)	(0.002)
School-oriented	0.101		0.044	0.026
	(0.002)		(0.002)	(0.002)
Math		0.156	0.150	0.122
		(0.001)	(0.001)	(0.002)
IQ				0.007
				(0.002)
Verbal				0.009
				(0.002)
Electives				0.051
				(0.002)
Outcome mean	10.570	10.570	10.570	10.570
Cohort FE	yes	yes	yes	yes
Adj. R^2	0.065	0.090	0.127	0.134
Observations	155704	155840	155097	154822

Notes: Each column reports the OLS regression results from Equation 13, with log earnings as the outcome. The model is estimated with truncated data using log earnings > 8 as the threshold. 'Action-oriented' is a composite of Sociability, Activity, and Masculinity. 'School-oriented' is a composite of Deliberation, Dutifulness, Achievement aim, Confidence, and Leadership. Test scores and traits are normalized to have mean 0 and standard deviation 1 within cohorts. Earnings are measured by averaging total labor and entrepreneurial income earned at age 35-38. Robust standard errors are reported in parentheses.