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IFAU INSTITUTE FOR EVALUATION OF LABOUR MARKET AND EDUCATION POLICY

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The different returns to cognitive ability in the labor and capital markets[a]

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Abstract

We investigate the returns to cognitive ability in the labor and capital markets. Using population-wide Swedish military enlistment data and administrative tax records, we find that cognitive ability is much better at predicting capital income than labor earnings. The difference is almost a factor of three and remains substantial even after controlling for education, occupation, savings, inheritance, and parental background. Moreover, ability is significantly positively correlated with wealth returns. Our results provide new insights into why inequality in capital income is greater than in labor income and shed light on the drivers of economic mobility.

Keywords: Ability, Skills, Education, Capital income, Wealth
JEL codes: J24, D31, H20

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1 Introduction

A vast literature in economics has studied how people's economic outcomes are affected by their innate abilities. Almost all attention has been paid to outcomes in the labor market.[1] Much less is known about the relationship between ability and capital market outcomes In a world where capital plays an increasingly important role in the economic position of households, especially at the top of the income distribution, a fundamental question is whether returns to ability differ across labor and capital markets. In other words, filling the knowledge gap about how individual skills matter for advancement in both the labor and capital markets is an important research task.

In this paper, we examine associations between individual cognitive ability, measured in young adulthood, and labor and capital income several decades later. The analysis uses unique population registers of cognitive ability recorded for Swedish men during their military enlistment at age 18. We match these records with market outcomes observed in administrative tax registers. It is important to measure different forms of labor and capital income, and our analysis considers annual earnings and monthly wages as well as several types of capital income (interest income, dividends, capital gains, and estimated returns to wealth using data on asset portfolios).

Our main finding is that individual cognitive ability matters significantly more for capital income than for labor earnings. This difference is observed across a wide range of specifications and income measures. The estimates suggest a return differential of a factor of three. The ability coefficients for labor income are 0.2, which is similar to previous studies, but they are almost 0.6 for capital income. With respect to participation, i.e. the probability of having positive labor or capital income, we find even larger differences.

Why is cognitive ability associated with higher returns in the capital market relative to the labor market? From the perspective of a simple life-cycle model, ability affects an individual's capital income through two primary channels: i) the savings channel, and, ii) the wealth return channel. The savings channel reflects the fact that more talented people tend to save larger amounts for a variety of reasons, such as higher labor income, more affluent parents, or a greater em-

[1]See, for example, Murnane et al. (1995), Cawley et al. (2001), Kuhn and Weinberger (2005), Heckman et al. (2006), and Lindqvist and Vestman (2011).

phasis on future consumption. The wealth return channel reflects that talented people make better investments and thus earn higher returns on their asset portfolios, either because ability has a direct impact on the quality of investments or because it has an indirect impact through educational and occupational choices.

Empirically, we shed light on the mechanisms behind the differential returns to ability in the labor and capital markets. First, controlling for prior savings, we find that the ability coefficient on capital income changes only marginally relative to our baseline specification. Second, we observe bequests for a subset of individuals and find that they have no effect on the estimated coefficients. Third, we include controls for education and occupation. Education controls reduce the ability coefficient by about half for both labor and capital income, while occupation controls imply a larger reduction for labor income than for capital income. In other words, skills acquired later in life cannot account for the differential returns to innate ability. Fourth, controlling for parental labor and capital income and comparing siblings in family fixed effects regressions shows that parental background is more important for the relationship between ability and capital market outcomes, although the difference between labor and capital returns to ability remains substantial, exceeding a factor of two. Fifth, using data on stock ownership, bank deposits, and housing wealth, we find that cognitive ability is significantly positively correlated with individual wealth returns.

We present three extensions of the main analysis. In the first, we analyze gender differences using high school grades instead of cognitive ability. The results show that there is a differential return to these grades in the labor and capital markets, and that the magnitudes are roughly the same for men and women. The second extension examines trends over 25 years and shows that the differential return to cognitive ability in the labor and capital markets is surprisingly robust over time. There is a slight upward trend in the ability coefficient for capital income, from 0.45 in the 1990s to 0.55-0.60 in the 2010s, while the coefficient for labor income is stable at 0.2 throughout the period. The third extension examines how the difference is affected by taxation and shows a larger after-tax difference, suggesting that the tax system exacerbates rather than mitigates the differential returns to cognitive ability in the labor and capital markets.

In terms of the related literature, virtually all previous studies have analyzed within-market returns to different abilities. Our contribution is to study between-market returns to cognitive ability.

Among the studies focusing on the labor market, two are particularly relevant to our work. Using the same Swedish military enlistment data that we use, Lindqvist and Vestman (2011) analyzed the differential returns to cognitive and non-cognitive abilities in the labor market and found that these two measures of ability are roughly equally important for labor earnings, but that non-cognitive ability is more important at the bottom of the earnings distribution and for employment outcomes.[2] Edin et al. (2022) used the same data to analyze trends in the returns to cognitive and non-cognitive ability in the Swedish labor market. They found that the relative return to non-cognitive ability has increased over time, a change they attribute to demand-side factors.[3] Relative to these two studies, we find very different results for the capital market. Cognitive ability is much more important than non-cognitive ability for most capital market outcomes, and about equally important for capital market participation. Moreover, we do not find an increasing trend in the relative importance of non-cognitive ability in the capital market.

A comparatively smaller literature has focused on returns to ability in the capital market. Among the more recent studies, Grinblatt et al. (2012), using Finnish military draft data, found that IQ is a significant driver of stock market performance. Barth et al. (2020), using data from the United States, calculated a "score" based on genetic endowments combined with educational attainment for 20,000 individuals and found that this score is related to wealth at retirement, an effect that persists after controlling for lifetime earnings and education. Fagereng et al. (2020) used Norwegian data to document substantial heterogeneity in wealth returns, even within narrow asset classes, but without explicitly linking this heterogeneity to individual cognitive ability.[4]

[2]Lindqvist and Vestman (2011) used LINDA, which is a representative panel dataset covering 3 percent of the Swedish population annually. They analyzed wages and labor earnings in 2006 for men born between 1965 and 1974 (excluding the self-employed, students, and workers in the agricultural sector). In our paper, we examine both labor and capital outcomes, but use population-wide data focusing on outcomes averaged over 2005-2007 and the 1951-1975 cohorts.

[3]In an earlier study, Deming (2017) found an increasing importance of social skills in the U.S. labor market.

[4]A few papers have examined the role of education for capital market outcomes. Cole et al. (2014) exploited exogenous variation in state compulsory schooling laws in the United States and found that education had a positive effect on a range of financial outcomes, arguing that this was driven by changes in saving or investment behavior rather than simply increased labor earnings. Black et al. (2018) used exogenous changes in compulsory primary schooling and

The rest of the paper is organized as follows. Section 2 describes the preliminaries of our analysis in the form of a simple life-cycle model, a description of our data, and the estimation strategies we employ. Section 3 presents the main results, and in section 4 we analyze the mechanisms. Extensions are presented in section 5 and finally, section 6 offers concluding remarks.

2 Preliminaries

2.1 A simple life-cycle model

Before turning to the empirical analysis, let us briefly illustrate how ability is likely to affect people's capital income in a standard life-cycle model, highlighting two basic channels: (i) the amount people save, and (ii) the returns people receive on their savings.

Suppose agents live for two periods, working in the first and retiring in the second. Each individual is endowed with a vector of skills θ and a vector of other characteristics ϕ that may affect behavior through preferences but do not affect returns in the labor or capital markets. An agent sells her skills in the labor market at some prices p^w, resulting in an hourly wage of $w(\theta, p^w)$. In the capital market, an agent can earn a return on investment equal to $r(\theta, p^k)$, where p^k is a vector of parameters that determine how a given vector θ is rewarded in the capital market in terms of the return that can be earned.[5] Empirically, we interpret r as the average return over all assets. The fact that r depends on the skill vector is uncontroversial and consistent with empirical evidence documenting substantial heterogeneity in returns, even within narrow asset classes (Fagereng et al. 2020).

In the labor market, exerting a labor supply of h implies a labor income of $w(\theta, p^w)h$ and a disutility of labor of $\xi(\theta, \phi)v(h)$, where v is strictly increasing and convex. In the capital market, saving an amount of s yields a return of

found that an additional year of education increased both financial market participation and the share of financial wealth allocated to stocks. Fagereng et al. (2021) exploited a Norwegian school reform in the 1960s that changed the length of compulsory schooling in Norway and found, in contrast, that schooling led to higher returns in the labor market but not in the capital market, suggesting the importance of non-acquired skills. Using a similar approach, Girshina (2019) examined the effect of education on wealth using Swedish data from 1999 to 2007.

[5] The implications of individual differences in r for the design of optimal labor and capital taxation have been analyzed by Gahvari and Micheletto (2016), and Gerritsen et al. (2022).

$r(\theta, p^k)s$. The utility from consumption is given by a standard CRRA function, and the coefficient of relative risk aversion is $\sigma(\theta, \phi)$.[6] Finally, the weight placed by the agent on second-period utility is equal to $\beta(\theta, \phi)$, and we assume that there is some other source of income in each period $t = 1, 2$ (e.g., inherited wealth), denoted by $y_t(\theta, \phi)$.[7]

Our formulation, which includes the vector ϕ, realistically captures the fact that even though higher-skilled individuals may have lower effort costs on average, there are also higher-skilled individuals who have higher effort costs (e.g., due to a high preference for work-life balance). It also captures the fact that even though high-skilled individuals on average tend to discount the future less than low-skilled individuals, some high-skilled individuals may discount the future heavily (for example, those with poor health).

Suppressing the dependencies on θ, ϕ, p^w and p^k for ease of notation, individuals choose hours of work h and savings s to maximize:

$$U = \frac{[wh - s + y_1]^{1-\sigma} - 1}{1 - \sigma} - \xi v(h) + \beta \frac{[rs + y_2]^{1-\sigma} - 1}{1 - \sigma},$$

where $\sigma > 1$. Optimal labor supply and savings can be written $h = h(\theta, \phi, p^w, p^k)$ and $s = s(\theta, \phi, p^w, p^k)$. The marginal effect of θ on labor earnings is:

$$\frac{d}{d\theta}(wh) = \frac{dw}{d\theta}h + w\frac{dh}{d\theta}, \tag{1}$$

where

$$\frac{dh}{d\theta} = \frac{dh}{dw}\frac{dw}{d\theta} + \frac{dh}{d\xi}\frac{d\xi}{d\theta} + \frac{dh}{d\sigma}\frac{d\sigma}{d\theta} + \frac{dh}{dy_1}\frac{dy_1}{d\theta}. \tag{2}$$

Thus, as can be seen from the right-hand side of (1), ability affects earnings not only through the wage rate, but also through labor supply. The labor supply response, decomposed in (2), consists of a wage effect, a taste-for-work effect, an effect of ability on consumption curvature (which affects the marginal utility of earning additional income), and an effect on non-labor income (which, since

[6] As we abstract from risk and portfolio choice, σ here serves to capture differences in preferences for intertemporal consumption smoothing.

[7] Empirically, discount factors differ across individuals, as shown, for example, by Epper et al. (2020). The implications of differences in β for the optimal design of the tax system have been explored by, for example, Diamond and Spinnewijn (2011) and Golosov et al. (2013).

leisure is a normal good, an increase in y_1 implies a traditional negative income effect on labor supply). The marginal effect of ability on capital income is

$$\frac{d}{d\theta}(rs) = \underbrace{\frac{dr}{d\theta}s}_{\textit{Wealth return channel}} + \underbrace{r\frac{ds}{d\theta}}_{\textit{Savings channel}}, \tag{3}$$

where

$$\frac{ds}{d\theta} = \frac{ds}{dw}\frac{dw}{d\theta} + \frac{ds}{dr}\frac{dr}{d\theta} + \frac{ds}{d\sigma}\frac{d\sigma}{d\theta} + \sum_{t=1,2}\frac{ds}{dy_t}\frac{dy_t}{d\theta} + \frac{ds}{d\beta}\frac{d\beta}{d\theta}. \tag{4}$$

The right-hand side of (3) reflects two effects: (i) an ability-gradient in the *return* to saving, and (ii) an ability-gradient in the *level* of saving. As can be seen from (4), the ability-gradient in the saving response is a combination of wage effects, rate-of-return effects, consumption curvature effects, changes in nonlabor income, and changes in intertemporal consumption preferences.[8]

2.2 Data

We use Swedish administrative register data on individual income, taxes, educational attainment, occupation, household status, and ability measures from military enlistment.[9] The study population consists of Swedish men born in 1951-1975 who participated in compulsory military service around the age of 18 and for whom we observe their cognitive ability scores. Observing individual abilities in young adulthood, i.e. before university enrollment and career choice, is a major advantage of our study. This explains why the Swedish military enlistment ability scores have been used several times in research before, and they have been found to be consistent over time, across other measures of ability, as well as correlated with a number of economic outcomes later in life.[10]

[8]The model could be extended in several directions. For example, the level of saving could be allowed to affect returns, which would be the case if people who save more have access to better savings opportunities, regardless of their innate ability to save (also known as "scale dependence"). This would create some overlap between the two channels above.

[9]For more details on our data sources, see Krigsarkivet, Enlistment register (1996), Statistics Sweden, Income and tax register (2007), Statistics Sweden, Higher education register (2000), Statistics Sweden, Occupation register (2006), Statistics Sweden, Monthly wage register (2007). The exact variable names we use in these registers are given in the appendix D3.

[10]See, for example, Lindqvist and Vestman (2011) and Edin et al. (2022) who analyze the relationship between cognitive ability and labor market outcomes.

Cognitive ability is measured in four different tests: (i) inductive ability (reasoning), (ii) vocabulary knowledge, (iii) spatial ability (metal folding), and (iv) technical comprehension. Each test result is measured on a 1-9 stanine scale. The draft board converts the scores from the subtests into an overall cognitive ability score, which is measured on a nine-degree normal distribution (stanine scale). In almost all of our analyses, we use this total score in our analysis, but re-standardize it so that it has a mean of zero. An exception is figure 1 below, where we use the raw sum of the subscores, which range from 4 to 36. The reason for this is that it provides more variation, which is helpful when creating a nonparametric plot. The total score is the official measure of cognitive ability used in the draft and is highly correlated with the sum of the subscores.[11]

In some specifications, we use other abilities measured at the time of military enlistment. These include non-cognitive traits assessed in personal interviews by psychologists,[12] and physical status, assessed in terms of height in centimeters.

Women are largely absent from the military enlistment data and are therefore not included in our main analysis. However, for those who have completed high school, we use high school GPA and math grades, measured around age 18, to examine gender differences in ability returns.[13] As we will see, the results (section 5.1) show quite similar patterns for men and women in our main outcomes.

Income data come from tax registers. Labor earnings consists of wages, salaries, sole proprietorship income, and includes taxable transfers such as sick leave and parental leave, but excludes pensions and unemployment insurance. Capital income is the sum of interest income from bank deposits and fixed-income securities, dividends from listed and non-listed corporations, and realized capital gains from the sale of either non-financial (real estate) or financial

[11] The correlation is 0.98. In our main analysis sample, 1,282,546 observations have an overall cognitive ability score, while 1,211,400 have scores on each of the four individual subtests.

[12] This process resulted in scores for an individual's social maturity, psychological energy, intensity, and emotional stability. We use the total score for all of these traits, measured on a stanine scale.

[13] GPA is available for individuals born in 1955-1975, and math grades are available for those born in 1967-1975. All grades are measured on a scale of 1-5, and we standardize them before including them in our analysis. For men, the correlation between cognitive ability and both grade measures is about 0.45.

assets. We supplement these income data in two ways. Monthly wages for full-time equivalent employees are collected from the separate wage register, which covers a subset of the working population and is administered by the Swedish National Mediation Office. Individual wealth returns are constructed by dividing taxable capital income by asset values derived from bank deposits, listed shares and housing, using the wealth register (see section 4.3 for details).

Data on educational attainment include the number of years of education and the field of education and are obtained from the Education Register at the National Agency for Education. Data on occupational classification are obtained from Statistics Sweden.

We also observe bequests in the Swedish Tax Agency's inheritance tax dataset. This dataset covers all inheritances received by all Swedish individuals who died between July 2001 and December 2005 and for whom an inheritance report or inheritance notification was submitted to the Swedish Tax Agency.

The analysis focuses on outcomes during 2005-2007, since we have access to individual wealth holdings for these years. This period implies that the men we study are 30 to 56 years old, i.e. of working age and old enough to have accumulated personal wealth. We have also used earlier and later time periods without finding significant differences in the results. An explicit analysis of trends in the relationship between ability and labor/capital income is provided in section 5.2. Descriptive statistics and sample attrition are presented in the online appendix (tables D1 and D2).

2.3 Estimation Strategy

We estimate the return to cognitive ability in labor earnings and capital income using log-linear regression models of the following type:

$$Y_{ia} = \alpha_a + \beta Cog_i + \gamma X_i + \varepsilon_{ia}. \tag{5}$$

The dependent variable Y_{ia} refers to the logarithmized market outcome for individual i in cohort a, where the market outcome is either labor earnings, capital income, or wealth returns. The parameter α_a is a cohort-dummy and we allow for the possibility of adding controls that are captured by the vector X.

The vast majority of men in our sample have labor earnings, but fewer have capital income. In our main analysis, we use log-transformed incomes, which means that zero observations are dropped. As a result, the earnings regressions are run on a larger population than the capital income regressions. To account for differences in participation, we separately estimate extensive margin regressions where the outcome variable is a binary indicator for having positive income.

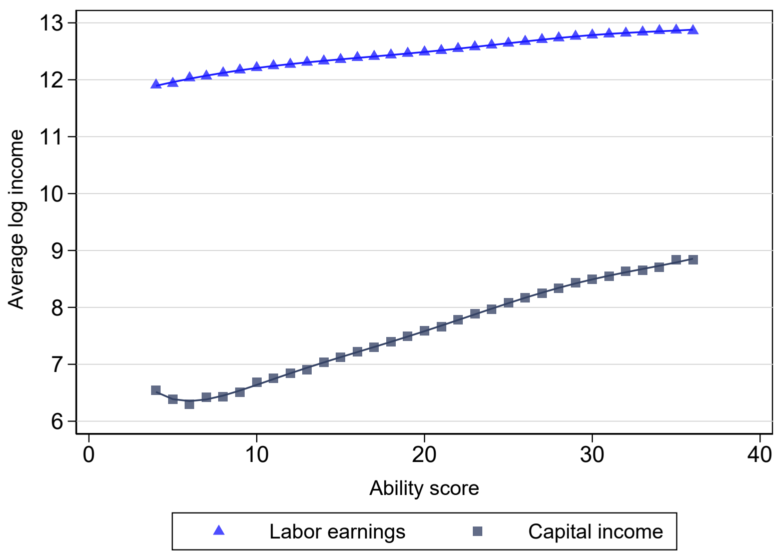
3 Main Results

We first show how cognitive ability is associated with labor and capital income. We then analyze how the results change when different forms of labor and capital income and other abilities are used.

3.1 Different Returns in the Labor and Capital Markets

The main result of our paper is presented in figure 1 below. The figure shows the relationship between individual cognitive ability test scores and average log labor and capital income. The two distinct slopes represent the different returns to ability in the labor and capital markets.

Figure 1: Labor earnings, capital income and cognitive ability.



Note: Labor earnings and capital income are in logarithms. In the appendix figure D2 we show the relationships in levels. The minimum possible score is 4 and the maximum is 36.

The above pattern is confirmed in the OLS regressions in table 1. We find that cognitive ability is much more strongly associated with capital income than with labor earnings. The estimated return to ability for labor earnings is 0.18, while it is 0.56 for capital income, a difference of a factor of three. This means that a standard deviation increase in individual cognitive ability is associated with a 20 percent increase in labor earnings and a 60 percent increase in capital income. The last two columns of the table show that this result is largely unaffected when we take into account the large difference in people's participation in the labor and capital markets. In our sample of adult men, 92 percent earn labor income but only 76 percent earn capital income. We will examine the participation rate in more detail below.

Table 1: Ability returns, labor earnings and capital income.

	(1)	(2)	(3)	(4)
			Labor earnings>0 and Capital income>0	
	Labor earnings	Capital income	Labor earnings	Capital income
Ability	0.183	0.560	0.161	0.550
	(0.001)	(0.003)	(0.001)	(0.003)
Obs	1,177,491	978,372	951,997	951,997
R^2	0.050	0.052	0.048	0.052

Note: Betas of $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. The dependent variable is annual log income, averaged over the period 2005-2007. "Labor earnings" includes wages, salaries and self-employment income in sole proprietorships, and includes sick leave and parental leave, but excludes pensions and unemployment insurance. "Capital income" includes interest income from bank deposits and other securities, dividends and realized capital gains. Column 1 is for individuals with positive labor income, column 2 is for individuals with positive capital income, while columns 3 and 4 are for individuals with both positive labor income and positive capital income.

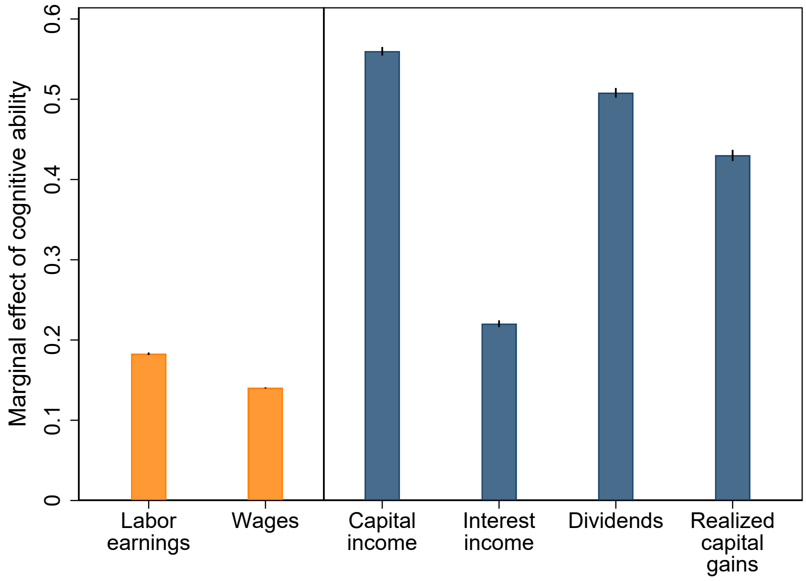
Additional robustness checks are presented in the appendix. Appendix section A.4 shows regressions in levels rather than logs, analyzes robustness to outliers, and excludes self-employed individuals. Appendix section A.5 estimates returns to ability for different subscores of cognitive ability available in the military enlistment data.

3.2 Different Forms of Labor and Capital Income

We now broaden the analysis by considering different forms of labor and capital income. This analysis is particularly important in the case of capital income, which consists of income from a variety of investments. Our main measure of capital income is the sum of interest income from bank deposits and fixed-income securities, dividend income from listed and unlisted corporations, and realized capital gains from the sale of financial and non-financial assets.[14] In this section we look at each of these individual subcomponents. We also complement our main measure of labor income by examining monthly full-time equivalent wages for employees.

Figure 2 shows that the differential return to cognitive ability in the labor and capital markets does not change much when the type of income considered is varied. Monthly wages and annual labor earnings have coefficients of about 0.15-0.2, and the different components of capital income have coefficients between 0.4 and 0.5. The highest return is found for dividend income, 0.51, and the second highest is the return on realized capital gains. Interest income is an exception, with an estimated ability return of 0.23, which is still statistically significantly larger than the ability return on labor earnings, but still smaller than for the other forms of capital income.

Figure 2: Ability returns, different forms of labor and capital income.



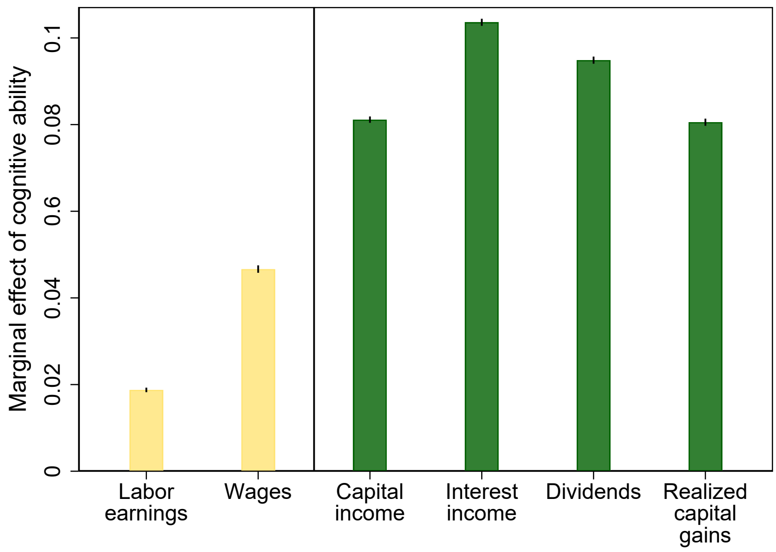
Note: Estimates from $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$ where the different measures of logged incomes Y are presented on the x-axis. For a detailed regression table, see appendix table A1.

[14]The concept of capital income we use closely corresponds to the variables observed in tax registers, but it could be further extended. For example, housing income could be included as imputed income from owner-occupied housing. We could also include a measure of unrealized capital gains.

3.3 The Participation Margin

We now turn to the participation margin, that is, the probability of having positive labor and capital income. Figure 3 shows the same pattern as table 1, namely a differential return to cognitive ability in the labor and capital markets. Notably, the result holds regardless of the type of labor and capital income considered. The probability of participation is higher for monthly wages than for annual earnings, but both coefficients are still significantly lower than for any of the capital market outcomes.

Figure 3: Ability returns, participation margin.



Note: Estimates from $\mathbf{1}[Y_{ia} > 0] = \alpha_a + \beta Cog_i + \varepsilon_{ia}$ where the various measures of income Y are plotted on the x-axis. A detailed regression table can be found in the appendix, see table A3.

3.4 Other Abilities

The ability to earn labor and capital income is related to a wide range of skills, not just the cognitive abilities considered in our main analysis. In this section, we extend the scope of our analysis by using information from military enlistment on two other innate individual abilities: non-cognitive (soft) skills, assessed by professional psychologists according to predefined schemes, and physical characteristics, here proxied by height.[15] Previous studies have examined the role of these abilities for labor earnings (Lindqvist 2012, Lundborg et al. 2014), but as far as we know there are no previous papers that have assessed their importance for capital income.

The left panel of figure 4 shows the relative returns to cognitive ability, non-cognitive ability, and height estimated in multivariate regressions using either labor earnings or capital income as the outcome variable. The results for labor earnings show that the relative returns to cognitive and non-cognitive ability are at similar levels, around 0.15. In contrast, for capital income, cognitive ability has a coefficient that is twice as large, 0.46, as non-cognitive ability, 0.24. Height is less correlated with both capital and labor income, but still has a larger coefficient for capital income.[16]

In the right panel of figure 4, we examine the relative returns to cognitive ability, non-cognitive ability, and height for the participation margin. We find that both cognitive and non-cognitive ability are significantly more associated with positive capital income than with positive labor earnings, but the difference is much larger for cognitive ability. Height is much less important for the extensive margin in both the labor and capital markets, although it is more important in the capital market.

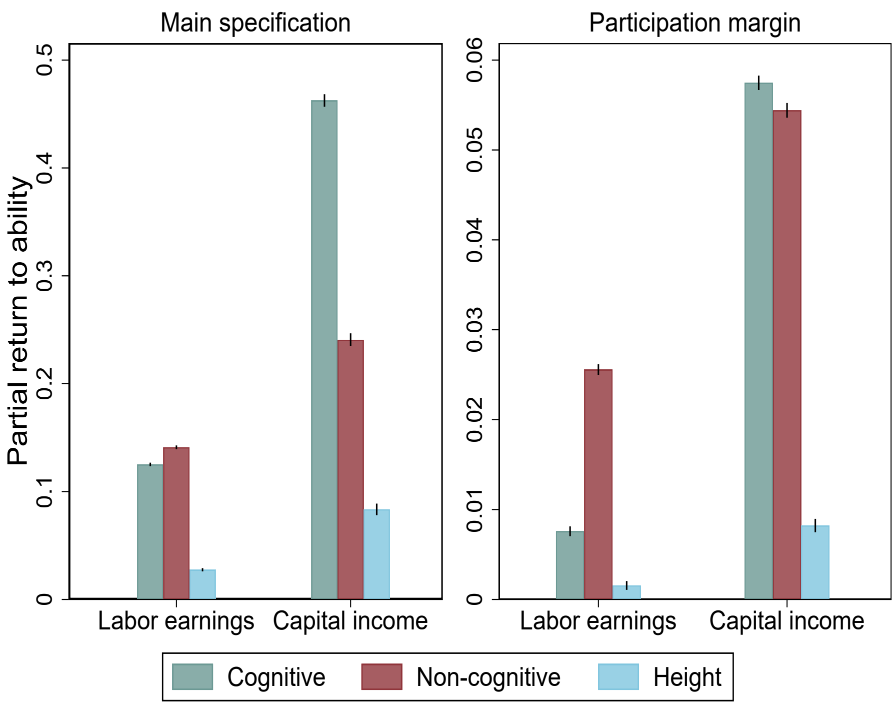
In sum, the exercise here underscores the special role that cognitive ability seems to play for capital market outcomes.[17]

[15] Cognitive and non-cognitive ability are positively correlated, with a correlation coefficient of about 0.38.

[16] One explanation for this could be that height is associated with the likelihood of holding managerial positions (Lindqvist 2012). This could generate capital income in the form of stock option programs.

[17] Further analysis looking at different forms of labor and capital income can be found in the appendix section A.1 and bivariate regressions on the return to different abilities are contained in the appendix section A.3.

Figure 4: The relative returns to different innate abilities.



Note: Estimates for the main specification from $Y_{ia} = \alpha_a + \beta^c Cog_i + \beta^n Non\text{-}cog_i + \beta^h Height_i + \varepsilon_{ia}$. A regression table is presented in appendix table A2. Estimates for the participation margin from $\mathbf{1}[Y_{ia} > 0] = \alpha_a + \beta^c Cog_i + \beta^n Non\text{-}cog_i + \beta^h Height_i + \varepsilon_{ia}$. We also present these results in the appendix table A4.

4 Mechanisms

In this section, we analyze the mechanisms behind the different returns to cognitive skills in the labor and capital markets. First, we conduct a mediation-type analysis focusing on the role of education, occupation, savings, and bequests (section 4.1), as well as the role of family background using controls for parental income and family fixed effects (section 4.2). Second, we examine whether there is a positive association between cognitive ability and wealth returns using data on asset portfolios (section 4.3).

4.1 Education, Occupations, Savings and Bequests

We begin by adding controls for acquired skills in the form of educational attainment and work experience. These are factors that affect both labor and capital market outcomes, but we are interested here in examining whether they matter for the differential ability return in the labor and capital markets.[18] The results are shown in table 2.

In column 2 of table 2, we see that adding education controls reduces the estimates for cognitive ability by half for both labor income (from 0.18 to 0.08) and capital income (from 0.56 to 0.26). This substantial drop confirms that formal postsecondary education is an important channel through which the association between ability and labor/capital income operates. In column 3, on top of the education controls, we add dummies for 113 different occupations. For labor earnings, the ability coefficient continues to fall from 0.08 to 0.03, implying that skills acquired through formal education and work experience account for 85 percent of the labor market return to cognitive ability. For capital income, adding occupations to education reduces the coefficient much less, from 0.26 to 0.17. Comparing 0.17 with 0.03, a difference of a factor of six, shows that the different return to cognitive ability is not diminished but rather increased by conditioning on formal acquired skills.

In columns 4-6, we add past savings (estimated using tabulated income-consumption data from the Swedish expenditure survey HUT) to the capital income regression testing the savings channel in equation (3). Column 4 shows that this reduces the ability coefficient by one fifth, from 0.56 to 0.45. This measure of savings is the closest we get to a direct test of the level of the savings channel (although we also shed light on this channel through our other analyses below). Adding the education and occupation controls in columns 5 and 6 reduces the ability coefficient to 0.15. Note that despite the large impact of these controls, there remains a substantial difference in the return to ability in the labor and capital markets. This can be seen by comparing 0.15 to the labor market return to ability in column 3, 0.029, which indicates that the differential return is at least a factor of four.

The role of inheritance is examined in columns 7 and 8. This analysis includes all men in our population who were registered as heirs during 2001-2005. In column 7, we examine the relationship between ability and capital income for

[18]While the important role of education and occupational experience for labor market outcomes is well established, education and occupational experience may also matter for capital market outcomes, as they may affect both saving behavior and asset returns in equation (3) through what is known in the financial economics literature as financial literacy, see, e.g., Lusardi et al. (2017) and Altmejd et al. (2022) for recent contributions.

this subsample, comparing heirs who received a positive amount with heirs who received nothing (about one-third of all registered heirs). The results show that bequests have no effect on the estimated ability coefficients, which together with the above results suggests that past capital accumulation, either through savings or bequests, is of limited importance for the different return to ability in the labor and capital markets.

Table 2: Ability returns controlling for education, occupations, savings and bequests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Labor earnings							
							Bequest sample	
Ability	0.183	0.081	0.029				0.188	0.186
	(0.001)	(0.001)	(0.001)				(0.002)	(0.002)
Bequest > 0								0.050
								(0.004)
Education	No	Yes	Yes				No	No
Occupation	No	No	Yes				No	No
Obs	1,177,491	1,168,514	1,037,410				219,950	219,950
R^2	0.050	0.104	0.266				0.050	0.051
	Capital income							
							Bequest sample	
Ability	0.560	0.261	0.170	0.454	0.218	0.148	0.580	0.550
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
Savings				0.671	0.621	0.654		
				(0.005)	(0.005)	(0.006)		
Bequest > 0								0.656
								(0.012)
Education	No	Yes	Yes	No	Yes	Yes	No	No
Occupation	No	No	Yes	No	No	Yes	No	No
Obs	978,372	969,793	854,951	971,454	965,043	852,780	189,191	189,191
R^2	0.052	0.090	0.124	0.090	0.118	0.146	0.053	0.068

Note: Betas from from $Y_{ia} = \alpha_a + \beta Cog_i + \gamma X_i + \varepsilon_{ia}$ where X includes control variables for educational attainment, occupation, estimated accumulated savings, and a dummy for receiving a bequest. Controls for education include both level and field of education. Controls for occupation are based on the three-digit codes in Statistics Sweden's occupational classification SSYK96. Savings are computed from tabulated income-consumption evidence in the Swedish Household Expenditure Survey (HUT), which estimates individual consumption and individual savings (which are logged) accumulated over the period 2000-2004. The "bequest sample" covers bequests to men born in 1951-1975 with a cognitive ability score at military enlistment and who are recorded as heirs in the Swedish Tax Agency's inheritance tax dataset.

4.2 Parental income and family fixed effects

Parental economic position is an important variable associated with both ability (through genetic and social intergenerational transmission of skills and traits) and success in labor and capital markets. For example, in the labor market, high-income parents may provide their children with social connections that are conducive to high-wage employment (see, for example, Plug et al. 2018). In the capital market, financially successful parents may provide their children with information about investment opportunities, thereby influencing their investment behavior and subsequent returns.[19]

In this section, we analyze how controlling for the parental economic position matters for the estimated differential return to ability in the labor and capital markets. We do this in two ways. First, we control for parental labor and capital income. Second, we compare siblings (brothers) by introducing family fixed effects.[20]

The results are shown in table 3. The regressions with parental income controls are presented in Panel A. They show that controlling for total parental labor income reduces the ability coefficient on labor earnings by 0.011 (a drop of about 6%), while the ability coefficient on capital income is virtually unaffected. Controlling for total parental capital income reduces the coefficient on labor income by 0.05 (a drop of 3%), while the coefficient on capital income is reduced by 0.108 (a drop of almost 20%). In Panel B, we control for family fixed-effects. In this exercise, in the case of labor earnings, the ability coefficient falls by about 0.04 (a drop of about 22%). In the case of capital income, the reduction is 0.241 (a reduction of about 42%).

The overall message of this analysis is that controlling for parental economic position reduces the returns to ability more for capital income than for labor earnings. This, of course, raises a new set of interesting questions about intergenerational mobility and persistent economic inequality that are beyond the scope of this paper. However, the results do not change the main finding of the paper, which is that there is a substantially different return to ability in the labor and capital markets. The differential rate of return remains above a factor of two, even after controlling for the economic position of the family.

[19]There is a large empirical literature documenting the intergenerational transmission of income and wealth. Examples of studies using Swedish data are Björklund and Jäntti (1997), Björklund et al. (2012), and Adermon et al. (2018). One reason for these correlations is surely that skills are partially inherited. Grönqvist et al. (2017) use a special Swedish longitudinal dataset called "Evaluation Through Follow-up" (ETF), which closely mirrors the military enlistment tests, and find a raw father-son correlation in cognitive ability between 0.32 and 0.35.

[20]The latter exercise should be interpreted with some caution as it controls for half of the genetic transmission, and an unknown part of the social family environment, which means that the identifying variation is somewhat special.

Table 3: Ability returns controlling for family background

Panel A: Parental income controls	(1)	(2)	(3)	(4)	(5)	(6)
		Labor earnings			Capital income	
Ability	0.183	0.172	0.178	0.560	0.560	0.452
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)
Parental labor earnings		0.069			0.026	
		(0.001)			(0.003)	
Parental capital income			-0.001			0.259
			(0.001)			(0.003)
Obs	1,177,491	1,157,083	251,504	978,372	961,791	226,523
R^2	0.050	0.055	0.045	0.052	0.053	0.075
Panel B: Family fixed-effects						
		Labor earnings			Capital income	
Ability	0.183		0.142	0.576		0.335
	(0.001)		(0.002)	(0.004)		(0.007)
Family FE	No		Yes	No		Yes
Obs	504,024		504,024	416,558		416,558
R^2	0.053		0.023	0.051		0.011

Note: In panel A, we control for average parental labor and capital income when the child is 16-20 years old. For individuals born in 1951, we use an average of parental income when the child is 17-20 years old because 1968 is the first year for which we have income data. Parental income controls are logarithmized.

4.3 Wealth Returns

Recent empirical studies have documented substantial heterogeneity in wealth returns. For example, Fagereng et al. (2020) found substantial return heterogeneity using Norwegian data, which they argue likely reflects differences in the ability to generate returns and knowledge of investment.[21] Moreover, estimating expected returns using an asset pricing model on Swedish data, Bach et al. (2020) found higher expected returns for wealthy households.

The results in table 2 of section 4.1 show that controlling for savings reduces the ability coefficient in the main capital income regression by about one-fifth. This suggests that ability is associated with higher capital income even for people with similar levels of savings, suggesting that there is an ability gradient in *wealth returns*.[22] The importance of the wealth returns channel is also suggested by the relatively large effect of the education and occupation controls in the capital income regression, as these variables are typically associated with financial sophistication conducive to high returns.

[21]Notably, they found that returns were heterogeneous, even within asset classes, and even when controlling for the risk and scale of investments.

[22]Of course, it could also reflect that we are only partially capturing individuals' actual savings due to measurement error in our savings variable.

We now explicitly investigate the relationship between cognitive ability and wealth returns by matching the Swedish data on individual ability with data on capital income and asset holdings. Following Fagereng et al. (2020), the return on asset k of individual i in the end of period t is defined as:

$$r_{it}^{k} = \frac{y_{it}^{k}}{\frac{1}{2} \cdot (w_{it-1}^{k} + w_{it}^{k})}. \tag{6}$$

The numerator is the asset-specific capital income (including capital gains), and the denominator is the average value of the asset between $t-1$ and t.[23] In this subsection, we use as our outcome variable $\bar{r}^k$ defined as the average of (6) over the period 2005-2007.[24]

We estimate returns on three specific assets: bank deposits, housing, and listed stocks. Interest income and the total value of bank deposits are observed in the tax registers. Housing income is set equal to the holding period return, which we calculate as the sum of rental income and capital gains (or losses) on the housing investment. The rental income is an imputed rate of return of 2.88 percent (Fagereng et al. 2020, Eika et al. 2020) on the value of the dwelling, and the capital gain is calculated as the change in housing wealth between two consecutive years, holding transactions constant. Listed stock returns, calculated for each individual company share, is the sum of dividends and accrued capital gains or losses during the year.

In table 4 we present the results using both the level of returns and the logarithm of returns as dependent variables. We can immediately see that higher cognitive ability is associated with higher returns, regardless of whether we use logs or levels. In order to facilitate the interpretation of panel a), the average return on each asset during 2005-2007 is shown below the results. For bank deposits, the average return is 1.09 percent, which means that 100 SEK in a bank account generates on average about 1 SEK in interest income. The aver-

[23]The reason for using the average wealth value over two periods, is that we do not know when, in a given year, any transactions took place.

[24]As in Fagereng et al. (2020), we impose some sample restrictions to enhance the economic relevance of the calculated returns. First, we avoid inflated returns due to exceptionally small levels of gross wealth by excluding observations with asset levels below 100 USD (1000 SEK) in each year. Second, we remove the top and bottom 0.5 percent of average returns to reduce the influence of outliers. For returns on bank deposits, we only trim the top since roughly 20 percent of the population have a return of zero, reflecting the economically relevant return on "salary accounts" that do not provide any interest.

age return on housing and listed shares is around 15 percent. Armed with these figures, we see that a one standard deviation increase in cognitive ability is associated with a 7.6 percent increase in bank returns (0.083/1.092), while the correlation between ability and housing returns is much smaller, 0.99 percent (0.144/14.59). For listed stocks, the correlation is 5.5 percent (0.833/15.28). The results in panel b) for log returns show a similar picture. We also find that there is considerable heterogeneity in returns, as measured by standard deviations.[25]

Table 4: Wealth returns and ability.

	(1) Bank return	(2) Housing return	(3) Listed stock return
		a) Returns	
Ability	0.083	0.144	0.833
	(0.001)	(0.014)	(0.068)
Obs	770,336	783,245	382,690
R^2	0.007	0.006	0.003
Mean	1.092	14.59	15.28
SD	1.050	11.97	39.94
		b) Log returns	
Ability	0.020	0.022	0.030
	(0.001)	(0.001)	(0.002)
Obs	613,870	740,849	268,137
R^2	0.001	0.008	0.001

Note: Panel a) uses returns in levels and shows results from regressions $r_{ia} = \alpha_a + \beta cog_i + \varepsilon_{ia}$. Panel b) uses log returns and shows results from regressions $\ln r_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. Returns are calculated as averages over the years 2005-2007.

The overall message of table 4 is that high ability individuals earn higher returns on their investments, which provides an explanation for why high ability individuals are more successful in the capital market. Note that the wealth-return channel operates through two primary pathways: (i) returns from higher risk-taking, and, (ii) returns from higher risk-adjusted returns. Our paper shows that both pathways are at play. As we have shown in section 3.3, high ability individuals are more likely to engage in risky investments, and in this section we have seen that high ability individuals earn higher returns even on investments that involve little or no risk (bank deposits).

[25] This is in line with what was previously documented for Norwegian investors by Fagereng et al. (2020).

To assess the importance of the wealth return channel for the different return to ability in the labor and capital markets, we include flexible controls for wealth returns in our main regression. The results are shown in table 5. In this analysis, we focus on a balanced sample for which we observe all three return categories (bank return, housing return, and stock return), which reduces the sample size. Nevertheless, comparing columns 1 and 5, we see that controlling for all three types of returns reduces the ability coefficient in the labor market by only about 2.8%, while the ability coefficient in the capital market is reduced by almost 20%. As shown by columns 2-4, this reduction is almost entirely driven by bank returns, and to a lesser extent by stock returns.

Table 5: Ability returns controlling for deciles of wealth returns

	(1)	(2)	(3)	(4)	(5)
	Labor earnings				
Ability	0.174	0.170	0.174	0.173	0.169
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bank return	No	Yes	No	No	Yes
Housing return	No	No	Yes	No	Yes
Listed stock return	No	No	No	Yes	Yes
Obs	234,815	234,815	234,815	234,815	234,815
R^2	0.062	0.067	0.063	0.064	0.068
	Capital income				
Ability	0.312	0.264	0.309	0.299	0.251
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bank return	No	Yes	No	No	Yes
Housing return	No	No	Yes	No	Yes
Listed stock return	No	No	No	Yes	Yes
Obs	237,530	237,530	237,530	237,530	237,530
R^2	0.034	0.104	0.043	0.056	0.132

Note: In columns 2, 3, and 4 we control for bank return, housing return, and listed stock return separately, and in column 5 we control for bank return, housing return, and listed stock return simultaneously. We have divided the sample into return deciles and we use return decile dummy variables when controlling for wealth return.

5 Extensions

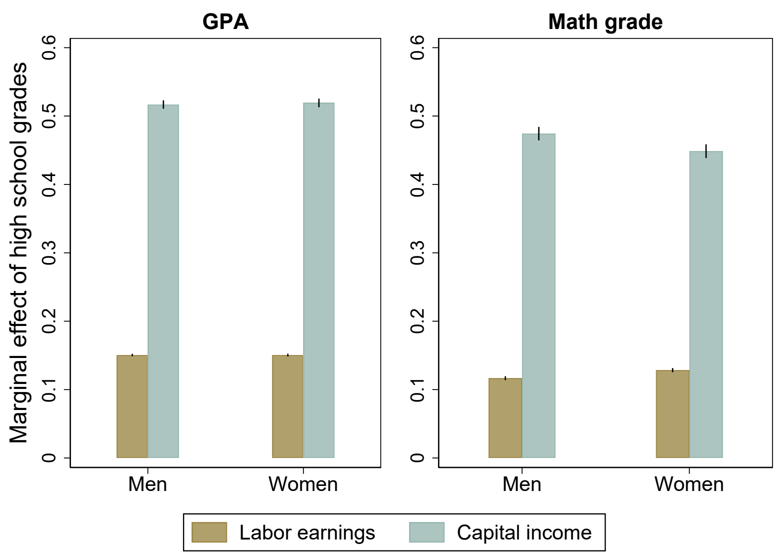
We present three extensions to the main analysis, looking at gender differences, trends over time, and potential pre- and post-tax differences.

5.1 Gender Differences

One limitation of military enlistment data is that it covers only males, which prevents general conclusions from being drawn for the population as a whole. We now attempt to analyze the patterns of ability returns for both men and women by proxying cognitive ability with high school grades, using either grade point averages (GPAs) or math final grades. At the same time, it should be recognized that school grades are not perfect proxies for enlistment measures, as they reflect classroom effort and social aspects of the learning environment.

Figure 5 shows the ability coefficients based on the same regression framework as in the main analysis, but using high school grades instead of enlistment data as the ability measure for men and women. The results show that the capital-labor differential in the return to ability is similar for men and women, regardless of whether we use GPA or math grades. It is interesting to note that the estimated coefficients using school grades are also similar in magnitude to the results obtained using military enlistment data. This lends additional credibility to the external validity of the main analysis.

Figure 5: Ability returns using GPA and math grades.



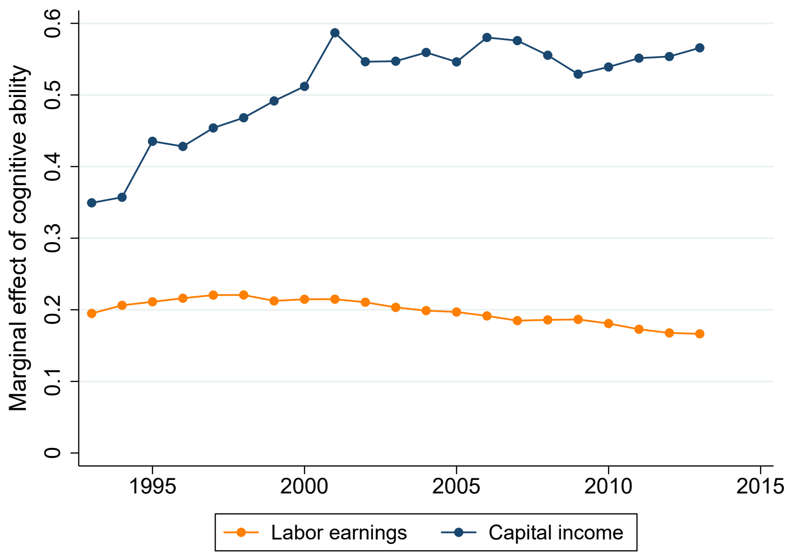
Note: Beta-coefficients estimated using $Y_{ia} = \alpha_a + \beta Grade_i + \varepsilon_{ia}$ where $Grade$ is GPA or math grade from high school. When we use GPA as a measure of ability, the sample consists of men and women born in 1955-1975 for whom we observe their high school GPA. When we use math grade as a measure of ability, the sample consists of men and women born 1967-1975 for whom we observe their high school math grade. A detailed regression table can be found in the appendix, see table B1.

5.2 Trends in the Differential Return to Ability

So far, our findings have been based on results from a specific time period, the mid-2000s. But how stable are our results over time? The Western world has experienced profound changes in the degree of trade globalization, financial liberalization, and technological progress, all of which may have affected how ability is rewarded in labor and capital markets. We now examine outcomes over a 25-year period, from the early 1990s to the mid-2010s. In order to follow cohorts of similar age in our enlistment data, we restrict the sample to men aged 38-42 and compute three-year moving earnings averages. We emphasize that this is only a first step in characterizing trends in ability returns in the labor and capital markets. For example, we do not account for changes in the composition of the sample population that occur as individuals move in and out of the labor and capital markets. In addition, we do not observe whether some sources of capital income, such as realized capital gains, are associated with transaction patterns that are correlated with trends in asset prices.

Figure 6 shows the trends in the return to cognitive ability in labor and capital income. A first result is that the return differential is visible throughout the period, indicating the overall robustness of the analysis in our paper with respect to the chosen time period. It also suggests that the return differential is a long-run result. A second result is that the return differential was relatively stable during the 2000s and 2010s, hovering around a factor of almost three. In the mid-1990s, however, the return on capital was lower and the differential was a factor of two.

Figure 6: Trends in ability returns.

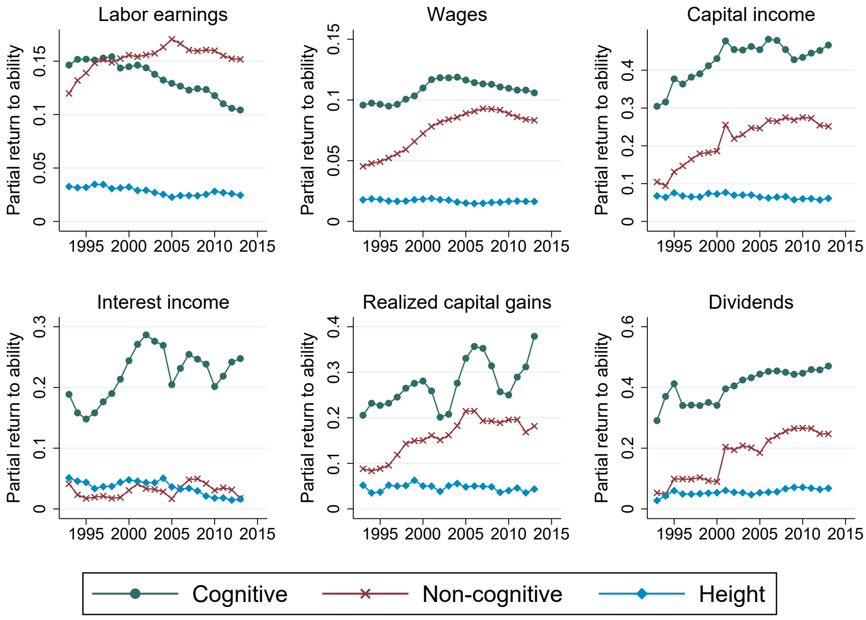


Note: The figure shows estimates $\hat{\beta}_t^a$ from $Y_{iat} = \alpha_{at} + \beta_t^c Cog_i + \varepsilon_{iat}$.

Figure 7 shows trends in ability returns for different forms of labor and capital income, including the other ability measures in our military enlistment data. We see that the relative return to non-cognitive ability in the labor market has become larger over time, a result previously highlighted by Edin et al. (2022).[26] Interestingly, we find no such pattern in the *capital market*. Cognitive ability was consistently the most important measure of ability in determining success in the capital market throughout the period analyzed and for all capital market outcomes.

[26]These authors suggest that individuals with high non-cognitive ability sort into high-paying occupations where abstract and social tasks are more common. Since occupations that rely on high cognitive skills are more exposed to offshoring, while tasks that require interpersonal communication skills are more difficult to outsource abroad, they argue that the demand for non-cognitive skills has increased, and thus the relative return to non-cognitive skills.

Figure 7: Trends in ability returns, other ability measures.



Note: Estimates $\hat{\beta}_t^a$ from $Y_{iat} = \alpha_{at} + \beta_t^c Cog_i + \beta_t^n Non\text{-}cog_i + \beta_t^h Height_i + \varepsilon_{iat}$.

5.3 Taxation

The ability measure we study is arguably quite close to what Mirrlees (1971) originally envisioned as the basis for redistribution in his seminal work on optimal taxation. In this section, we compute ability associations using pre- and post-tax outcomes to assess the extent to which labor and capital taxes redistribute according to cognitive ability. We also analyze whether the actual tax system mitigates or exacerbates the different returns to ability in the labor and capital markets.

Table 6: Ability return before and after tax.

	(1)	(2)	(3)	(4)
	Taxable labor earnings		Taxable capital income	
	Pre-tax	Post-tax	Pre-tax	Post-tax
Ability	0.157	0.131	0.393	0.393
	(0.001)	(0.001)	(0.004)	(0.004)
Obs	1,192,381	1,192,381	325,654	325,654
R^2	0.075	0.053	0.054	0.052

Note: Incomes are in logarithmic form and averaged over the period 2005-2007. The regression specification is the same as in table 1. Taxable labor income before taxes includes both labor income and transfers before taxes, and after-tax income is calculated by subtracting all central and local government taxes less deductions. Taxable capital income differs from our main capital income concept in that it includes deductions for interest expenses and we subtract capital income taxes. All data on taxes paid come from administrative tax registers.

The results are shown in table 6. In the first two columns we consider a broad measure of labor income, including both earnings and taxable transfers, and we see that the after-tax return to ability falls. This implies that the taxation of labor income contributes to ability-based redistribution. In columns three and four we repeat the analysis for capital income. In this case, the after-tax correlation is the same as the post-tax correlation, implying that capital taxation does not contribute to ability-based redistribution.[27] We thus conclude that the tax system exacerbates rather than mitigates the different returns to cognitive ability in the labor and capital markets.[28]

6 Concluding Remarks

While an extensive economic literature has examined the relationship between individual ability and labor market outcomes, very few studies have analyzed

[27]These results are partly mechanical, since labor income taxation is progressive by design, while capital income taxation is proportional (in line with the dual income tax structure of the Swedish tax system), and high-ability individuals tend to have both higher labor and capital income. However, high-ability individuals also tend to avoid being subject to the progressive labor income tax code, for example by shifting income from the labor to the capital income tax base, see Bastani and Waldenström (2021).

[28]In the Appendix section B.2, we provide a complementary analysis using taxes paid as the dependent variable. This analysis shows that a one standard deviation increase in cognitive ability increases labor taxes by 21%, capital taxes by 30.7%, and total taxes by 21.6%. When controlling for labor earnings, the estimates for total taxes and capital taxes fall to 8.8% and 23.1%, respectively.

ability and capital market outcomes, and none have compared the relative returns to ability in the two markets.

We find that cognitive ability is much better at predicting capital income than labor income, and that this result is robust across a wide range of outcome measures and specifications. Since inequality is greater in capital income than in labor income, our results show that it is essential to consider individual cognitive ability in order to understand the drivers of overall income inequality. Moreover, if one wants to understand the drivers of intergenerational persistence of economic status, our results underscore the need to analyze both labor and capital income.

There are interesting avenues for further research. For example, there is evidence that technology and trade have increased the importance of non-cognitive skills relative to cognitive skills among wage earners. However, it is largely unknown how technical progress and financial globalization have affected the returns to different skills in the capital market. Moreover, the differential returns to ability in the labor and capital markets have implications for the optimal mix of taxes on labor and capital in the context of Mirleesian tax policy design. We hope to continue working on these and other related issues in the future.

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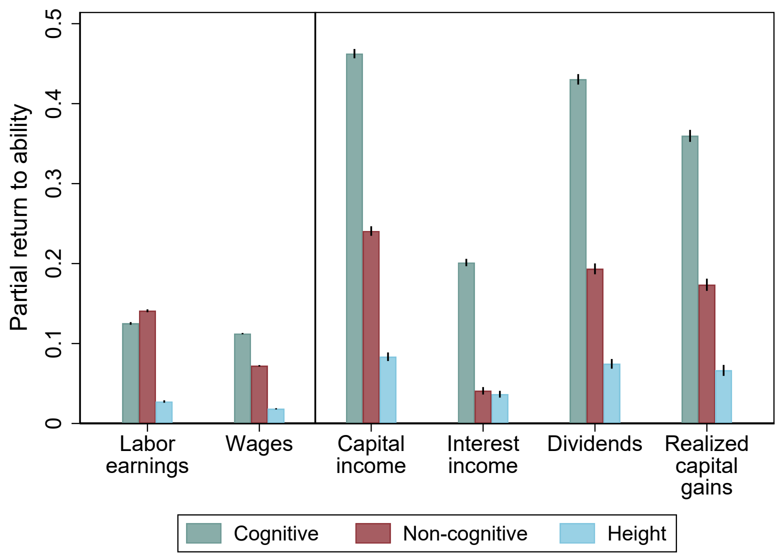
A Supplementary Material for Section 3

A.1 Other abilities and different forms of labor and capital income, intensive margin

Figure A1 shows the relative importance of different abilities for different forms of labor and capital income along the intensive margin.

Figure A1: Relative returns to different abilities, different forms of labor and capital income



Note: Betas from $Y_{ia} = \alpha_a + \beta^c Cog_i + \beta^n Non\text{-}cog_i + \beta^h Height_i + \varepsilon_{ia}$.

Table A1: Regression table, different forms of labor and capital income.

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor earnings	Wages	Capital income	Interest income	Dividends	Realized capital gains
Ability	0.183	0.140	0.560	0.220	0.508	0.430
	(0.001)	(0.000)	(0.003)	(0.002)	(0.003)	(0.004)
Obs	1,177,491	625,744	978,372	718,575	758,905	561,599
R^2	0.050	0.182	0.052	0.029	0.051	0.042

Note: Beta-coefficients obtained from $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. These results are also presented in figure 2.

Table A2: Regression table, relative returns to different abilities.

	(1)	(2)
	Labor earnings	Capital income
Cognitive	0.125	0.463
	(0.001)	(0.003)
Non-cognitive	0.141	0.241
	(0.001)	(0.003)
Height	0.028	0.083
	(0.001)	(0.003)
Obs	1,141,374	951,117
R^2	0.075	0.059

Note: Betas from $Y_{ia} = \alpha_a + \beta^c Cog_i + \beta^n Non\text{-}cog_i + \beta^h Height_i + \varepsilon_{ia}$. These results are also presented in figure 4.

A.2 Other abilities and different forms of labor and capital income, participation margin

Table A3: Regression table, different forms of labor and capital income, participation.

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor earnings	Wages	Capital income	Interest income	Dividends	Realized capital gains
Ability	0.019	0.047	0.081	0.104	0.095	0.081
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	1,282,546	1,282,546	1,282,546	1,282,546	1,282,546	1,282,546
R^2	0.014	0.009	0.037	0.044	0.038	0.027

Note: Betas from $\mathbf{1}[Y_{ia} > 0] = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. These results are also presented in figure 3.

Table A4: Regression table, relative returns to different abilities, participation.

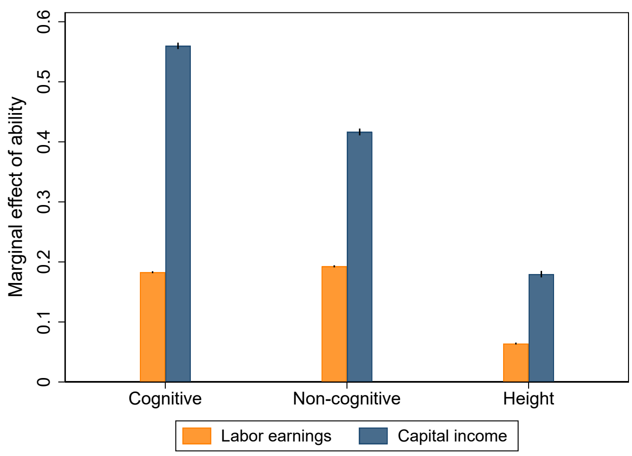
	(1)	(2)
	Labor earnings	Capital income
Cognitive	0.008	0.057
	(0.000)	(0.000)
Non-cognitive	0.026	0.054
	(0.000)	(0.000)
Height	0.002	0.008
	(0.000)	(0.000)
Obs	1,241,704	1,241,704
R^2	0.021	0.050

Note: Betas from $1[Y_{ia} > 0] = \alpha_a + \beta^c Cog_i + \beta^n Non\text{-}cog_i + \beta^h Height_i + \varepsilon_{ia}$. These results are also presented in figure **??**.

A.3 Bi-variate regressions, other abilities

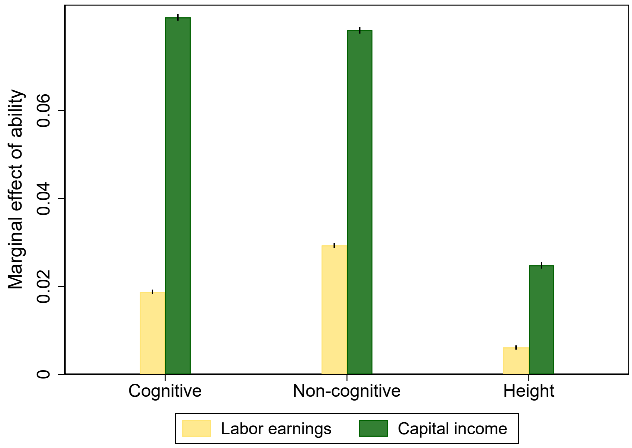
We now present bi-variate regressions of the returns to different abilities (instead of looking at the *relative* returns, as in the main text). See figure A2 for the intensive margin and A3 for the participation margin.

Figure A2: The returns to different abilities in bi-variate regressions.



Note: The beta-coefficients are estimated by the regression: $y_{ia} = \alpha_a + \beta Ability_i + \varepsilon_{ia}$.

Figure A3: The returns to different abilities in bi-variate regressions, participation.



Note: The beta-coefficients are estimated from the regression: $1[Outcome > 0] = \alpha_a + \beta Ability_i + \varepsilon_{ia}$.

A.4 Extra Robustness Checks

Table A5: Ability returns excluding the top one percent.

	(1) Labor earnings	(2) Capital income
Ability	0.169 (0.001)	0.533 (0.003)
Obs	1,165,717	968,543
R^2	0.045	0.049

Note: The dependent variable is annual log income, averaged over the period 2005-2007, *but excluding the top one percent*. "Labor earnings" includes wages, salaries and self-employment income in sole proprietorships, and includes sick leave and parental leave, but excludes pensions and unemployment insurance. "Capital income" includes interest income from bank deposits and other securities, dividends and realized capital gains.

Table A6: Ability returns using outcomes in levels.

	(1) Labor earnings	(2) Capital income
Ability	66.34	16.94
	(0.25)	(0.54)
Obs	1,229,466	1,233,825
R^2	0.073	0.001
Mean	318.50	33.53
Beta/Mean	0.21	0.51
Median	296.0	0.95
Beta/Median	0.22	17.83

Note: The dependent variable is annual income in *levels* (100 USD), averaged over the period 2005-2007. "Labor earnings" includes wages, salaries and self-employment income in sole proprietorships, and includes sick leave and parental leave, but excludes pensions and unemployment insurance. "Capital income" includes interest income from bank deposits and other securities, dividends and realized capital gains.

Table A7: Ability returns using outcomes in levels and excluding the top one percent.

	(1) Labor earnings	(2) Capital income
Ability	54.02	6.02
	(0.15)	(0.04)
Obs	1,217,196	1,221,448
R^2	0.107	0.022
Mean	304.17	16.22
Beta/Mean	0.18	0.37
Median	294.70	0.91
Beta/Median	0.18	6.62

Note: The dependent variable is annual income in *levels* (100 USD), averaged over the period 2005-2007, *and excluding the top one percent*. "Labor earnings" includes wages, salaries and self-employment income in sole proprietorships, and includes sick leave and parental leave, but excludes pensions and unemployment insurance. "Capital income" includes interest income from bank deposits and other securities, dividends and realized capital gains.

Table A8: Returns to ability excluding self-employed.

	(1)	(2)	(3)	(4)
	Labor earnings			
Ability	0.183	0.186	0.189	0.192
	(0.001)	(0.001)	(0.001)	
Owners of closely held corporations	Yes	No	Yes	No
Incorporated business owners	Yes	Yes	No	No
Obs	1,177,491	1,085,200	1,050,566	971,842
R^2	0.050	0.050	0.055	0.055
	Capital income			
Ability	0.560	0.551	0.591	0.582
	(0.003)	(0.003)	(0.003)	(0.003)
Owners of closely held corporations	Yes	No	Yes	No
Incorporated business owners	Yes	Yes	No	No
Obs	978,372	893,446	870,838	798,178
R^2	0.052	0.052	0.056	0.056

Note: In column 1, self-employed (denoted by "Self") are included. In column 2, we exclude owners of closely held corporations. In column 3, we exclude incorporated business owners. In column 4, we exclude both owners of closely held corporations and incorporated business owners. We define owners of closely held corporations from the variable BKUFOAB. Unincorporated business owners are defined using the income variables NAKTE and NAKTHB.

A.5 Sub-scores of cognitive ability

As mentioned in section 2.2, in our main analysis, we have used an overall cognitive ability stanine score calculated by the military enlistment authority based on the four cognitive ability sub-scores. Table A9 estimates the relative returns on the intensive margin for the sub-scores of the cognitive ability measure. The results show that all subcomponents are better in predicting capital income than they are in predicting labor income, although logical thinking is most important.

Table A9: Relative returns to sub-scores of cognitive ability.

	(1)	(2)
	Labor earnings	Capital income
Logical thinking	0.059	0.152
	(0.001)	(0.002)
Verbal knowledge	0.024	0.095
	(0.001)	(0.002)
3D comprehension	0.007	0.033
	(0.001)	(0.002)
Technical comprehension	0.023	0.075
	(0.001)	(0.002)
Obs	1,123,569	936,120
R^2	0.053	0.054

Note: Betas from $Y_{ia} = \alpha_a + \beta^l Logic_i + \beta^v Verbal_i + \beta^{3D} 3D_i + \beta^t Technical_i + \varepsilon_{ia}$. The sub-scores are standardized with mean zero.

B Supplementary Material for Section 5

B.1 Regression table, ability returns using GPA and math grades

Table B1: Regression table, ability returns using GPA and math grades.

	(1)	(2)	(3)	(4)
Panel A: GPA				
	Men		Women	
	Labor earnings	Capital income	Labor earnings	Capital income
GPA	0.151	0.517	0.150	0.519
	(0.001)	(0.003)	(0.001)	(0.003)
Obs	808,474	695,439	766,343	651,889
R^2	0.049	0.051	0.046	0.053
Panel B: Math				
	Men		Women	
	Labor earnings	Capital income	Labor earnings	Capital income
Math	0.117	0.474	0.128	0.449
	(0.001)	(0.005)	(0.002)	(0.005)
Obs	275,646	241,913	264,555	229,484
R^2	0.039	0.040	0.034	0.036

Note: Beta-coefficients estimated using $Y_{ia} = \alpha_a + \beta Grade_i + \varepsilon_{ia}$ where $Grade$ is GPA or math grade from high school. When we use GPA as an ability measure the sample consist of men and women born 1955-1975 for whom we observe their GPA. When we use math grades as an ability measure the sample consist of men and women born 1967-1975 for whom we observe their math grade. These results are also presented in figure 5.

B.2 Taxation: Additional Results

Table B2: Ability and paid taxes

	(1) Total taxes	(2) Total taxes	(3) Labor taxes	(4) Labor taxes	(5) Capital taxes	(6) Capital taxes
Ability	0.216	0.088	0.210	0.058	0.307	0.231
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Lab. earnings		0.672		0.751		0.350
		(0.002)		(0.003)		(0.005)
Obs	1,218,274	1,174,698	1,208,202	1,172,710	440,836	423,764
R^2	0.076	0.597	0.080	0.677	0.044	0.061

Note: Taxes are in log form and averaged over the period 2005-2007. The regression specification is the same as in table 1. All data on taxes paid are from administrative tax registers. Total tax is the sum of paid labor and capital taxes. Labor taxes are the sum of all central and local government taxes.

C Supplementary Material: Additional Data Description

C.1 Descriptive Statistics

Table D1: Descriptive statistics

	Mean	S.D	Min	P25	P50	P90	P99	Max
Cognitive ability	-0.00	1.00	-2.11	-0.58	-0.06	1.47	1.99	1.99
Birth year	1963.2	7.2	1951	1957	1964	1973	1975	1975
Labor earnings	31.9	25.3	0.0	22.2	29.6	51.9	106.6	2955.8
Wages	2.9	1.5	1.2	2.2	2.5	4.3	8.1	122.5
Interest income	0.1	1.3	0	0	0.01	0.3	1.7	1075.3
Dividends	0.9	30.5	0	0	0.00	0.6	12.8	28596.2
Realized capital gains	2.4	43.0	0	0	0	2.9	34.2	35278.0
Years of education	11.90	2.12	7.00	11.00	11.00	15.00	17.00	19.00

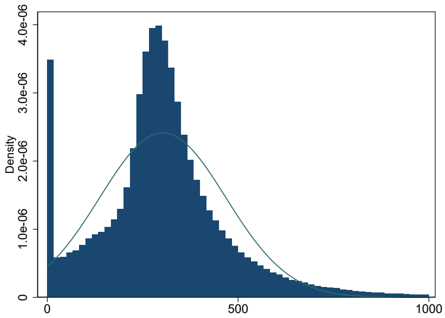
Note: All monetary variables are in 1000 USD.

Table D2: Attrition in the sample population (number of individuals)

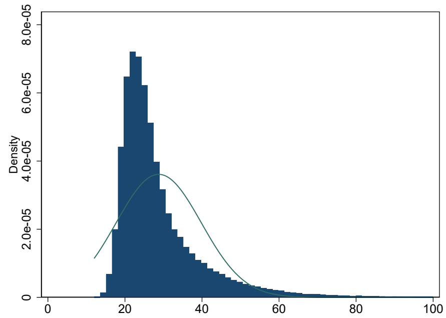
(1). Men born in Sweden 1951-1975 in population registry	1,421,627
(2). Men in (1) with a cognitive ability score in military enlistment	1,282,546
(3). Men in (2) with labor earnings > 0 (in 2005-2007)	1,177,491
(4). Men in (3) with non-missing information about level and field of education	1,168,514
(5). Men in (4) with non-missing information about occupation	1,037,410
(6). Men in (2) with capital income > 0 (in 2005-2007)	978,372
(7). Men in (6) with non-missing information about level and field of education	969,793
(8). Men in (7) with non-missing information about occupation	854,951
(9). Men in (2) with taxable capital income > 0 (in 2005-2007)	341,756

Note: For participation in different incomes and wealth components, see number of observations in regression tables.

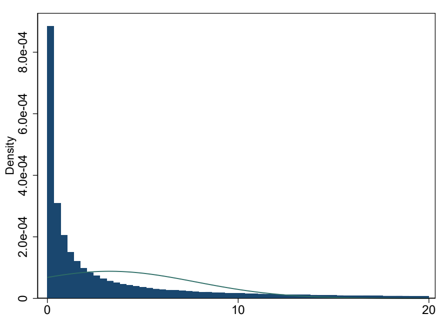
Figure D1: The distribution of labor and capital market outcomes



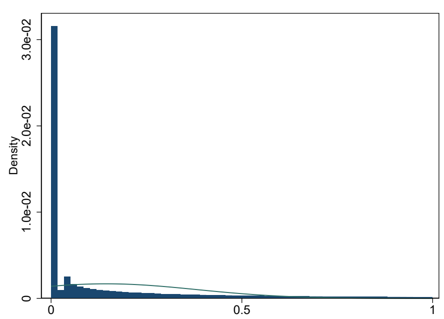
(a) Labor earnings



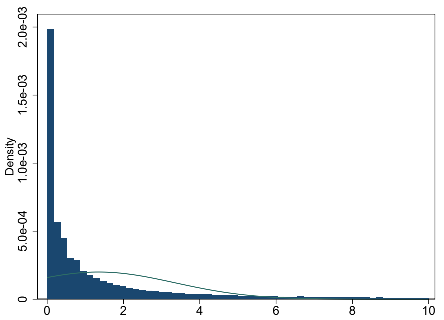
(b) Wages



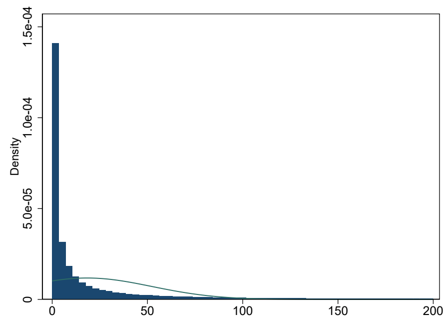
(c) Capital income



(d) Interest income



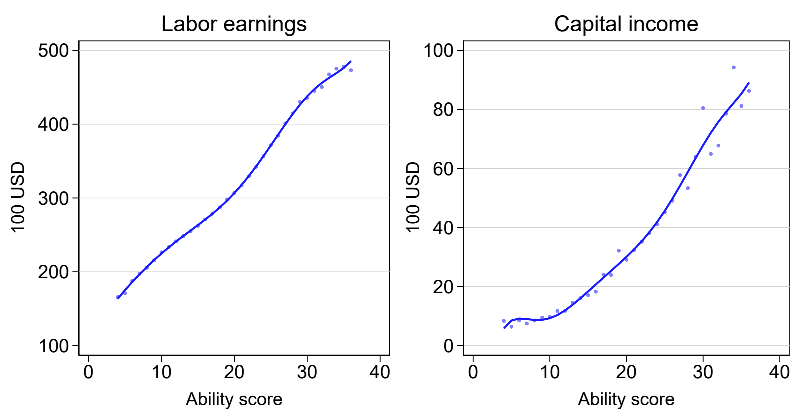
(e) Dividends



(f) Realized capital gains

Note: All variables are in 1000 USD and averaged over the years 2005-2007. *Labor earnings* above 100000 USD have been excluded and represent 1.2 percent of the sample. *Wages* above 10000 USD have been excluded and represent 0.5 percent of the sample *Capital incomes* with value zero or above 2000 USD have been excluded and represent 43 percent of the sample. *Interest income* above 100 USD have been excluded and represent 19.6 percent of the sample. *Dividends* with value zero or above 1000 USD have been excluded and represent 45.9 percent of the sample. *Capital gains* are realized capital gains from financial and non-financial assets. Values of zero and larger than 20000 USD have been excluded and represent 56 percent of the sample.

Figure D2: Cognitive ability score and labor/capital income.



Note: Labor earnings and capital income in hundreds of USD. The minimum points achievable is 4 and the maximum is 36. Figure 1 in the main text shows the association between ability and log labor earnings/capital income.

Table D3: Variables from the Income and Tax Register

Variables	Variable name in register
Labor earnings	CARB
Taxable labor earnings	CTXFVI
Labor earnings after tax	CTXFVI - SKLFVI - SSFVI
Interest income from bank deposit	KKURTA
Interest income from securities	KKUVP
Interest income	KKURTA + KKUVP
Dividends	KKUUTD
Realized capital gains	KV
Capital income	KKURTA + KKUVP + KKUUTD + KV
Taxable capital income	KKAP
Capital income after tax	KKAP - SKAP
Total tax	SSLUT