Cognitive Ability in Labor and Capital Markets*

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Abstract

How does the reward to cognitive ability in the capital market compare to its reward in the labor market? Using Swedish registry data linking enlistment test scores to tax records, we find that ability predicts labor income more strongly in percentile ranks (9.6 versus 7.3 ranks per standard deviation), but in logs the capital gradient is three times larger as logs amplify variation near zero, while ranks compress high-income differences. To understand the channels, we decompose the ability–capital income association. Controlling for labor income, a one standard deviation increase in ability predicts 21% higher saving among savers and 0.5 percentage points higher portfolio returns among stock investors, reflecting risk-adjusted performance rather than greater risk-taking. The results suggest that cognitive ability confers a direct advantage in capital markets beyond its role in labor income, with implications for inequality and taxation.

JEL Codes: D31, G11, J24, J31

Keywords: Cognitive ability, capital income, labor income, wealth inequality, saving behavior, investment returns

*Financial support from the Swedish Research Council, the Jan Wallander and Tom Hedelius Foundation and the IFN Tax Program is gratefully acknowledged. We are grateful for comments from Adrian Adermon, Adam Altmejd, Jesper Böjeryd (who suggested the decomposition framework), Mikael Elinder, Johannes Hagen, Mårten Palme, Uwe Sunde, Björn Öckert, seminar participants at IFAU, Helsinki GSE, Uppsala University, Erasmus University Rotterdam, Umeå University, as well as from conference participants at the IIPF conference in Tampere. We thank John Friedman for suggesting the risk-adjusted return analysis.

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1 Introduction

How valuable is cognitive ability in capital markets compared to labor markets? A large literature has documented the role of ability in labor market success, for example through earnings, employment, and occupational sorting.[1] A separate strand of literature has linked ability to financial outcomes such as stock market participation, portfolio returns, and wealth accumulation.[2] These two strands of literature have developed largely in isolation, leaving the central comparative question unanswered. The answer matters for understanding wealth inequality, optimal tax design, and the channels through which ability shapes economic disparities. If ability is associated with higher capital income through saving behavior and investment performance, not merely through higher labor income, then ability-related wealth inequality may be larger, and operate through different mechanisms, than labor income differences alone would suggest.

This paper studies these questions using Swedish administrative data that link military enlistment records of cognitive ability in young adulthood to comprehensive tax records covering labor income, capital income, and wealth holdings over 1998–2007. The data cover 1.24 million men, allowing us to observe labor income, capital income, and detailed financial portfolios for the same individuals. Because the two income types have very different distributions, we employ several complementary approaches to compare ability's associations with each. We then decompose the capital income association into an indirect channel operating through labor income and direct channels operating through saving rates and investment returns, using detailed wealth data to quantify these mechanisms.

We find that cognitive ability robustly predicts capital income, though the comparison with labor income depends on the metric chosen. In rank-based comparisons, which compress right-tail differences where capital income diverges most, a one standard deviation increase in ability is associated with moving up 9.6 percentile ranks in the labor income distribution and 7.3 ranks in the capital income distribution. In log specifications, this pattern reverses: the capital-income coefficient is substantially larger, partly because the log transformation magnifies variation near zero, where capital income has considerable density. We present log and level specifications, rank regressions, and a decomposition of extensive versus intensive margins. A three-part decomposition shows that approximately 90 percent of ability's association with capital income operates through the intensive margin.[3]

[1] See, for example, Murnane et al. (1995); Cawley et al. (2001); Kuhn and Weinberger (2005); Heckman et al. (2006); Lindqvist and Vestman (2011); Edin et al. (2022).

[2] See, for example, Grinblatt et al. (2011, 2012); Christelis et al. (2010); Fagereng et al. (2020); Barth et al. (2020).

[3] We subject the relationship between ability and both income types to a series of robustness checks. Both gradients decline when controlling for education and occupation, parental income, and sibling fixed effects, but the qualitative patterns are preserved. Results are robust to excluding self-employed individuals and outliers. Using high school GPA as a proxy for ability available for both genders, similar patterns emerge for women. A lifecycle analysis shows that labor income coefficients increase for young cohorts over time, consistent with employer learning, while capital income coefficients are relatively stable across age groups.

What drives the association between ability and capital income? Ability predicts not only higher labor income, which mechanically shapes saving capacity, but also higher saving rates and better investment performance *conditional on income*. Even if ability operated solely through labor income, saving rates that rise with income would generate some ability gradient in capital income. The observed association substantially exceeds this mechanical benchmark. We develop a decomposition framework that attributes the excess to saving and return channels operating beyond the labor income effect. Controlling for labor income, a one standard deviation increase in cognitive ability is associated with 21 percent higher saving among those with positive saving, and significantly lower rates of hand-to-mouth behavior. Among stock investors, the same ability increase predicts 0.5 percentage points higher annual returns, also conditional on income. Comparing unconditional and conditional estimates, approximately 42 percent of ability's total association with saving operates indirectly through higher labor income; for investment returns, income plays essentially no role.

The return advantage enjoyed by high-ability investors reflects superior stock selection rather than greater risk tolerance. High-ability individuals achieve higher risk-adjusted excess returns (α) while holding portfolios with slightly lower systematic risk (β). They are also more likely to participate in financial markets (ownership of financial assets rises from 82 percent in the lowest ability group to 97 percent in the highest) and hold more diversified portfolios. Ability strongly predicts participation in risky assets but not the share allocated to risky assets conditional on participation, suggesting that the extensive margin of financial market engagement is the key channel through which ability shapes portfolio composition.

The findings bear on two broader questions: the origins of wealth inequality and the design of tax policy. Capital income constitutes a large and growing share of total income in modern economies (Piketty and Saez, 2003; Elsby et al., 2013; Karabarbounis and Neiman, 2014; Bergholt et al., 2022; Grossman and Oberfield, 2022) and is highly concentrated among wealthy individuals (Saez and Zucman, 2016). If ability predicts capital income through saving and return channels that are largely independent of labor income, then ability-related wealth inequality may be substantially larger than labor income differences alone would suggest. For tax policy, the standard Mirrlees framework ties optimal schedules to the ability–earnings relationship in labor markets (Mirrlees, 1971). Our results indicate that ability also predicts capital accumulation and portfolio returns through channels not captured by that relationship, which is directly relevant to debates over the relative taxation of labor and capital income. Sweden's dual income tax system illustrates the point concretely: as we show, progressive labor taxes substantially compress the after-tax labor gradient, while proportional capital taxes leave the capital gradient intact.

Related Literature. Our work builds on two strands of research. We extend the extensive literature on labor market returns to ability. Foundational work by Murnane et al. (1995), Cawley et al. (2001), Kuhn and Weinberger (2005), and Heckman et al. (2006) established that cognitive ability significantly predicts earnings, with Farber and Gibbons (1996) and Altonji and Pierret (2001) showing that the coefficient on ability increases with labor market experience as employers learn about worker productivity (with similar patterns documented in Sweden by Falch and Sandgren Massih, 2012). Two studies using Swedish military enlistment data similar to ours are particularly relevant.[4] Lindqvist and Vestman (2011) find that cognitive and non-cognitive abilities are roughly equally important for labor earnings, though non-cognitive skills matter somewhat more at the lower end of the earnings distribution and for employment. Edin et al. (2022) document that the relative return to non-cognitive ability has increased over time, attributed to demand-side factors. Our results suggest a different pattern in capital markets, though differential measurement precision across the two ability types complicates the comparison, as we discuss in Section 7.

Second, we contribute to research examining ability's role in financial markets. Grinblatt et al. (2011, 2012) use Finnish population-wide data to demonstrate that IQ strongly predicts both stock market participation and investment performance. Christelis et al. (2010) provide comparable evidence for Europe. Barth et al. (2020) show that a genetic/educational attainment score relates to retirement wealth, controlling for earnings and education.[5] The broader literature has documented considerable heterogeneity in asset returns across households, without explicitly linking it to cognitive ability (Fagereng et al., 2020; Smith et al., 2019; Bach et al., 2020; Smith et al., 2023). Some research emphasizes education's role in financial decision-making (Cole et al., 2014; Black et al., 2018; Fagereng et al., 2026; Girshina, 2019). We contribute by decomposing the capital-income association into the underlying channels of saving and returns, identifying which financial behaviors account for the ability gradient.[6]

The paper proceeds as follows. Section 2 presents our decomposition framework, establishing the benchmark prediction. Section 3 describes our data. Section 4 presents the association between ability and labor and capital income using multiple complementary approaches. Section 5 implements the decomposition framework, estimating the indirect channel (through labor income) and direct channels (saving rates and investment returns). Section 6 examines specific financial behaviors underlying these patterns. Section 7 presents robustness checks. Section 8 concludes.

[4] Lindqvist and Vestman (2011) used a smaller representative panel dataset covering 3% of the Swedish population annually, analyzing wages and earnings in 2006 for men born 1965–1974. We use population-wide data and focus on outcomes averaged over 1998–2007 for the 1951–1975 cohorts, examining both labor and capital outcomes.

[5] Lindqvist et al. (2018) investigate how ability correlates with investment in the Swedish funded public pension plan, finding that non-cognitive ability predicts opting out of the default fund, while cognitive ability predicts portfolio overhaul, but with lower returns for higher non-cognitive ability.

[6] In a related spirit, Hartog et al. (2010) compare returns to cognitive and social skills across entrepreneurs and employees in the NLSY.

2 Decomposition Framework

We organize our empirical analysis using a simple accounting framework that decomposes how ability affects capital income. This framework guides our empirical strategy and establishes a benchmark for what we would expect if ability affected capital income only indirectly through labor income.

Consider individuals who earn labor income, save some fraction, and earn returns on saving. Each individual has ability θ, which may affect their wage w, labor supply h, saving rate Φ, and investment return R.

Labor income is $Z_L = w \cdot h$. Individuals save $s = \Phi \cdot Z_L$ and earn capital income $Z_K = R \cdot s = \Phi \cdot Z_L \cdot R$. In logarithms, these expressions become

$$z_L = \ln Z_L = \ln w + \ln h, \quad z_K = \ln Z_K = \phi + z_L + r, \tag{2.1}$$

where $\phi = \ln \Phi$ and $r = \ln R$.

The marginal effect of ability θ on log capital income is:

$$\frac{dz_K}{d\theta} = \frac{dz_L}{d\theta} + \frac{d\phi}{d\theta} + \frac{dr}{d\theta}. \tag{2.2}$$

Ability affects capital income through two channels: indirectly through labor income (which affects both the saving rate and the level of saving), and directly through saving behavior and investment returns.[7]

Benchmark: No Direct Effects. Suppose ability affects capital income only through labor income, with saving rates and returns responding to income but not directly to ability. If $\Phi = A_1 Z_L^{b_1}$ and $R = A_2 Z_L^{b_2}$, then:

$$\frac{dz_K}{d\theta} = (1 + b_1 + b_2)\frac{dz_L}{d\theta}. \tag{2.3}$$

In this benchmark, the capital coefficient equals $(1 + b_1 + b_2)$ times the labor coefficient, where b_1 and b_2 are the elasticities of saving rate and return with respect to income. This benchmark is restrictive: it rules out channels such as financial sophistication, portfolio sorting, income-risk differences, or latent financial skill. Less restrictive specifications, for example allowing saving rates to respond differently to ability at different income levels, would yield a higher benchmark

[7] The saving rate may also vary with ability through differences in time preferences. For heterogeneity in discounting and wealth inequality, see Epper et al. (2020). Heterogeneity in returns could reflect differences in entrepreneurial talent, stock-picking acumen, or the ability to avoid common financial mistakes. Empirical studies document that many individuals fail to diversify, pay excessive fees, and exhibit low financial sophistication (Benartzi and Thaler, 2001; Calvet et al., 2007, 2009; Goetzmann and Kumar, 2008; Von Gaudecker, 2015; Lusardi et al., 2017; Barber et al., 2005; Choi et al., 2010). Returns heterogeneity also helps reconcile lifecycle models with observed wealth inequality (Gabaix et al., 2016; Benhabib et al., 2019).

even without direct ability effects on investment returns.

Direct Effects. Now allow ability to directly affect saving rates and returns by adding ability terms to the benchmark specification. In logs, the saving rate and return become

$$\phi = a_1 + b_1 z_L + m_1 \theta, \quad r = a_2 + b_2 z_L + m_2 \theta, \tag{2.4}$$

where m_1 and m_2 capture direct effects of ability on log saving rate and log return, holding income constant. The total effect becomes:

$$\frac{dz_K}{d\theta} = (1 + b_1 + b_2)\frac{dz_L}{d\theta} + m_1 + m_2. \tag{2.5}$$

If $m_1 + m_2 > 0$, the observed differential exceeds the benchmark, indicating direct effects of ability on financial behavior.

Our empirical strategy proceeds in three steps: estimating total effects of ability on labor and capital income (Section 4), implementing the decomposition to quantify b_1, b_2, m_1, and m_2 (Section 5), and examining specific financial behaviors that might explain the direct effects (Section 6).

Several interpretive points deserve emphasis. First, our estimates are conditional correlations, not causal effects. Cognitive ability is measured at age 18, before education and career choices, which mitigates common endogeneity concerns. However, ability may proxy for other factors (risk preferences, discount rates, income uncertainty, or latent financial skill) that independently affect financial behavior. Second, the log-additive structure embeds specific functional form assumptions: saving rates and returns are modeled as power functions of income and linear functions of ability. The benchmark and its excess are defined relative to these assumptions. Third, the decomposition assumes that saving rates respond to total income regardless of whether that income was generated by ability or by other factors. We therefore view the framework as a useful organizing device that guides our empirical strategy, not as a structural model with causal interpretation.

3 Data

3.1 Data Sources and Study Population

We use Swedish administrative register data linking military enlistment records to comprehensive tax and wealth registers spanning 1998–2007. The study population consists of Swedish men born between 1951 and 1975 who participated in compulsory military examinations around age 18. Our data cover 1.24 million individuals, representing approximately 87 percent of men in these birth cohorts.[8] A key advantage is that we observe cognitive ability assessments before university enrollment, career choices, and income-generating years, minimizing reverse causality concerns. Because military enlistment covers only men, we verify in Section 7 that the pattern extends to women using high school GPA as an alternative ability measure.[9]

3.2 Ability Measurement

Cognitive ability is assessed through four tests during military enlistment: inductive reasoning, verbal knowledge, spatial ability, and technical understanding. The Swedish military combines these into an overall score on a 1–9 stanine scale. We re-standardize to mean zero and standard deviation one. All specifications include birth cohort fixed effects, absorbing any systematic cohort differences including potential Flynn effects (Rönnlund et al., 2013; Hermo et al., 2022). Appendix Table A8 confirms that within-cohort standardization has minimal impact on the individual coefficients, indicating no significant Flynn effect confound. The correlation between the stanine score and the sum of the four subscores is 0.98; 1,186,120 of the 1,243,270 men have scores on all four individual subtests. Results broken down by subcomponent appear in Appendix Table A9.

We also measure non-cognitive ability based on assessments by trained psychologists evaluating social maturity, psychological energy, intensity, and emotional stability. Height is measured during enlistment. The correlation between cognitive and non-cognitive ability is 0.38. Results using all three measures appear in Appendix Table A10.

Educational attainment (years and field) comes from the Education Register of the National Agency for Education; occupational classification comes from Statistics Sweden. Bequests are observed in the Swedish Tax Agency's inheritance tax records, covering inheritances from individuals who died between July 2001 and December 2005.

3.3 Income Data

Labor income comprises wages and active business income from sole proprietorships and partnerships, excluding social insurance benefits such as sick pay and parental leave.[10] We focus on market income from active labor supply.

The Swedish tax registers record capital income as a broad net measure: interest income,[11]

[8] Attrition from the enlistment population occurs primarily due to severe physical and mental disabilities that exempted individuals from testing and military service, with additional attrition from incomplete linkage to income tax registers. See online appendix Table A28 for a detailed breakdown, Table A29 for variable definitions, and Table A30 for the corresponding register variable names.

[9] GPA is available for individuals born 1955–1975, and math grades for those born 1967–1975. Both are measured on a 1–5 scale and standardized before use. For men, the correlation between cognitive ability and GPA is 0.45.

[10] The specific register variables are listed in Appendix Table A30.

[11] Swedish banks are not required to report interest income below 100 SEK (approximately $10) to the tax authority, so individuals with very small bank deposits may appear as having zero interest income in our data.

dividend income, and net realized capital gains,[12] minus capital losses and debt interest, plus imputed rents from owner-occupied housing.[13] Approximately 29% of individuals have negative average capital income under this broad measure, primarily driven by mortgage interest exceeding other capital returns (see Appendix Figure A6 for the distribution of individual components). Given the interpretive challenges posed by housing components (discussed below), our baseline measure is *financial capital income*: dividends, interest income, and net realized capital gains only. Under this measure, approximately 20% of observations are non-positive.

Housing wealth and mortgage debt play a conceptually ambiguous role in our capital income measure. A high-ability individual who earns more labor income can purchase a larger home with a larger mortgage. Even if equally skilled as an investor, this individual will have *more negative* housing capital income, not because of poor investment decisions but because of greater consumption of housing services. In Sweden's illiquid rental market, homeownership is often the primary means of accessing housing, making the distinction between housing consumption and investment particularly difficult to draw.[14]

A component-level decomposition (Appendix Table A1) confirms that the ability gradient is strongest for purely financial components (dividends: 0.58, capital gains: 0.46, interest: 0.37) and weakest for housing-related components (imputed rents: 0.23). Components that enter negatively (capital losses: 0.25, debt interest: 0.18) also show positive ability gradients, consistent with high-ability individuals being more active market participants. Our mechanism analysis in Section 5 similarly focuses on saving and returns in *financial assets only*, excluding housing wealth and mortgage transactions.

3.4 Saving and Portfolio Returns

Following Kolsrud et al. (2020), we split wealth changes into active saving (changes in quantities) and passive returns (price appreciation). The value of asset k for individual i at time t is $A_{ikt} = p_{kt}Q_{ikt}$, where p_{kt} is the price and Q_{ikt} is the quantity held. The change in asset value can be expressed as:

$$\Delta A_{ikt} = p_{kt}Q_{ikt} - p_{kt-1}Q_{ikt-1} = p_{kt}\Delta Q_{ikt} + \Delta p_{kt}Q_{ikt-1}. \tag{3.1}$$

Additionally, from 2006–2007, only holdings above 10,000 SEK were reported. This reporting threshold is unlikely to materially affect our results, as the amounts involved are small relative to average capital income.

[12]In the tax register, realized capital gains and losses are recorded as separate variables. For individuals whose realized gains exceed their losses, the loss can be deducted from the gain, so the data reflect the net amount.

[13]Imputed rents are computed by multiplying housing wealth by an assumed 6.5% annual return. Owner-occupied housing includes both single-family homes and cooperative apartments (*bostadsrätter*), the latter representing approximately 10% of owner-occupied properties in the sample.

[14]Negative capital income from mortgages reflects a combination of housing consumption choices, access to credit markets (itself a function of labor income), expected capital appreciation, and geographic sorting. On the last point, if high-ability individuals sort into jobs in high-growth areas, the resulting house price appreciation would generate a correlation that reflects location choice rather than investment skill (cf. Fagereng et al., 2019, 2025). The "jump" in average ability around zero broad capital income partly reflects the transition from renters (with near-zero capital income) to homeowners with net negative housing income.

This expression splits the change in value into an *active* saving channel, $p_{kt}\Delta Q_{ikt}$, and a *passive* capital gains channel, $\Delta p_{kt}Q_{ikt-1}$. We define saving and returns as:

$$S_{it} = \sum_{k=1}^{K} p_{kt}\Delta Q_{ikt}, \quad R_{it} = \frac{\sum_{k=1}^{K} p_{kt}Q_{ikt-1}}{\sum_{k=1}^{K} p_{kt-1}Q_{ikt-1}}. \tag{3.2}$$

We construct these measures using annual data on holdings of bank accounts, stocks, bonds, mutual funds, and private retirement accounts, recorded at end-of-year values.[15] Our analysis focuses on saving in financial assets, excluding changes in housing wealth and debt, as the latter primarily reflect mortgage transactions.[16] When debt is included, measured net saving can be negative for individuals whose debt payments exceed their asset accumulation; this typically reflects mortgage-related transactions (taking on housing debt) rather than dissaving from financial assets. In principle, negative measured saving could also arise from asset types not observed in the wealth registry (e.g., vehicles, home improvements, or unlisted business assets), though the financial assets covered account for the large majority of household wealth. Appendix Table A26 reports results including debt.

3.5 Sample and Summary Statistics

Our analysis uses 10-year averages of all income variables constructed over 1998–2007. During this period, the men in our sample range from age 23 (youngest cohort at the start of the period) to age 56 (oldest cohort at the end), corresponding to prime working years. Using 10-year averages reduces the influence of transitory income shocks and business cycle fluctuations. Saving and portfolio return measures are available for 2000–2007 only, because the underlying wealth data required to compute quantity changes begin in 1999.

The full linked sample contains 1,243,270 men.[17] Observation counts differ across specifica-

[15]For stocks, bonds, and mutual funds, we match individual holdings to asset-level price data using the ISIN code, which is available for approximately 50% of financial assets. For bank accounts, saving is calculated as the net change in holdings less interest earned. Before 2006, bank account holdings were reported only if interest payments exceeded 100 SEK; from 2006, all holdings above 10,000 SEK were reported, leading to a large increase in observed bank wealth. To avoid a spurious spike in measured saving, we censor 2006–2007 bank account holdings using the pre-2006 reporting rule (following Kolsrud et al., 2020). Averaged over eight years, the remaining reporting differences have only a marginal effect on the saving measure. For assets without specific price data, saving is estimated using average returns. Private pension saving is directly observed. Financial derivatives are assumed to have no return. When computing portfolio returns, we do not exclude assets that an individual no longer owns in year t but did own in $t-1$, as this would confound price changes with saving decisions. We exclude retirement savings in the public pension system and in collectively managed occupational plans that cannot be accessed before retirement.

[16]For more details on the saving measure and validation against national accounts aggregates, see Kolsrud et al. (2020) and Gareis et al. (2023). Appendix C.2 compares our microdata measures to national accounts data.

[17]The analysis draws on a large number of register variables that could not all be linked to a single dataset due to data access restrictions across research environments. Appendix Tables A10, 11, A12, A16, and A17 are therefore estimated on a separately constructed dataset. The baseline specification (Table 2) has been estimated on both datasets, yielding virtually identical coefficients (0.209 versus 0.207 for labor income; 0.649 versus 0.653 for capital income).

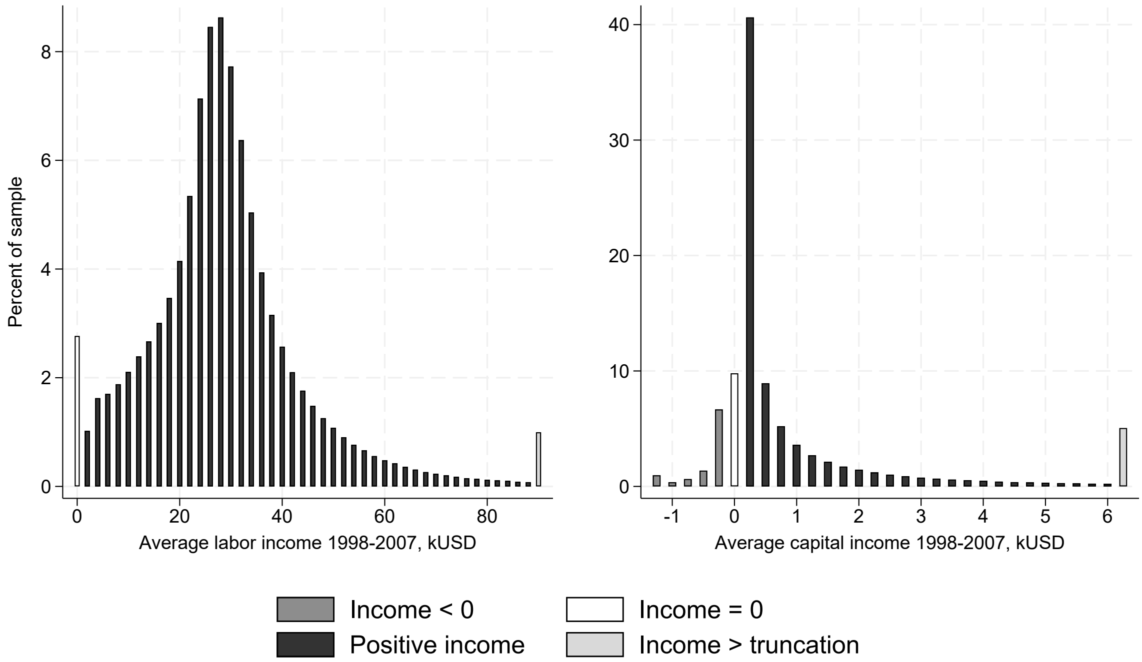
tions because log regressions require positive outcomes, rank and level regressions include zeros and negatives, and the saving and return analyses additionally require wealth and portfolio observability. The main log specifications use 1,214,246 men with positive labor income and 996,679 with positive financial capital income. Table 1 presents summary statistics. Notable features include: (1) the large standard deviation of capital income relative to its mean, reflecting the long right tail; (2) the approximately 20% share of observations with non-positive financial capital income (10% negative, 10% zero; see Appendix Table A6 for characteristics of these groups); and (3) the variation in saving behavior, with 26% having non-positive saving. Figure 1 illustrates the contrasting distributions of labor and capital income.

Table 1: Descriptive Statistics.

	Mean	S.D.	Min	P25	P50	P90	P99	Max	Positive share
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	
Years of education	11.90	2.12	7.00	11.00	11.00	15.00	17.00	19.00	
Labor income	27.11	19.82	0.00	18.19	25.52	44.27	86.93	3,808	0.98
Capital income	2.06	41.17	-695.11	0.00	0.10	2.95	26.85	27,125	0.80
Saving	1.18	26.65	-11,805	0.00	0.40	4.13	22.25	10,328	0.74
Portfolio returns	5.22	1,089	-4,550	0.00	0.11	2.90	52.24	620,876	0.44

Sample: 1,243,270 men born 1951–1975. All monetary variables in thousands of USD, averaged over 1998–2007. Saving and returns measured 2000–2007. Saving and portfolio return statistics include zeros for non-participants; the positive share column shows the fraction with positive values. Labor income is defined as wages plus active business income (see Appendix Table A30 for register variable definitions). For the log-transformed dependent variables used in regressions: log(labor income) has mean 3.08, SD 0.90 (N = 1,214,246 with positive values); log(capital income) has mean -1.78, SD 2.69 (N = 996,679 with positive values).

Figure 1: The Distribution of Labor and Capital Income.



Values in thousands of USD, averaged over 1998–2007. The graphs truncate labor income at the 99th percentile. Capital income is truncated at the 1st and 95th percentiles. These restrictions are applied for visual clarity; all regressions use full untrimmed samples. See Appendix Table A2 for a detailed breakdown.

4 Ability Gradients in Labor and Capital Income

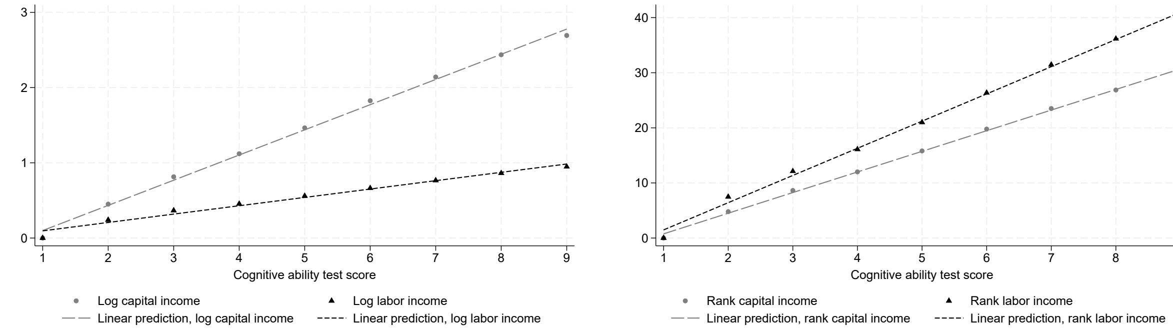
This section documents the association between cognitive ability and both income types using four complementary approaches: log specifications, level specifications, rank regressions, and an extensive-versus-intensive margin decomposition. Table 5 at the end of this section collects the results.[18]

4.1 Descriptive Patterns

Figure 2 plots mean log income and mean income rank against the nine cognitive ability stanine scores, with both series normalized to zero at the lowest score. In the log specification (Panel a), the capital income gradient is roughly three times steeper than the labor income gradient. In the rank specification (Panel b), the ordering reverses: the labor income gradient is steeper, because the heavy right tail of capital income compresses rank differences.

[18] As emphasized in Section 2, all estimates in this section are conditional correlations. Cognitive ability may proxy for other factors that independently affect financial outcomes.

Figure 2: Ability and Income: Log and Rank Specifications.



(a) Log specification

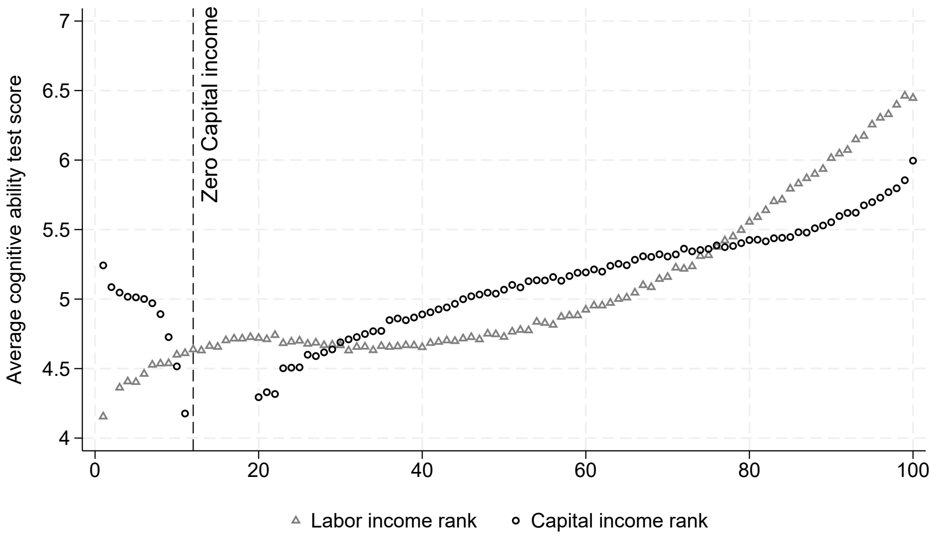
(b) Rank specification

Binscatter plots of income against cognitive ability (stanine scores 1–9). Both panels normalize the lowest ability group to zero. Panel (a): log labor income and log capital income (positive values only). Panel (b): within-sample income rank (percentile). Circles denote capital income; triangles denote labor income. Dashed lines show linear predictions. Averages over 1998–2007.

Figure 3 provides a complementary perspective, plotting average cognitive ability across percentiles of the labor and capital income distributions. Interestingly, the relationship between ability and rank flattens at the top of the labor distribution but strengthens at the top of the capital distribution.[19] The downward-sloping segment among low capital income individuals (those with negative financial capital income) likely reflects more active financial market participation: high-ability individuals hold more stocks and realize larger capital losses, generating more negative financial capital income (see Appendix Table A6 for characteristics of these groups and Appendix Table A1 for the positive ability gradient in capital losses). Appendix Figure A7 shows analogous patterns for non-cognitive ability.

[19] At the very top percentiles of capital income (above roughly the 97th percentile), average ability declines slightly. This likely reflects large one-time realized capital gains (e.g., from selling a business or property) that raise capital income irrespective of cognitive ability.

Figure 3: Cognitive Ability Along the Income Distribution.



Average cognitive test scores across income percentiles. Each percentile contains approximately 12,400 observations; 95% confidence intervals for the means are approximately ±0.02 test score points and would not be visible at the scale of the figure.

4.2 Log and Level Specifications

We regress income on cognitive ability:

$$Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}, \tag{4.1}$$

where Y_{ia} is an income measure for individual i in birth cohort a, Cog_i is cognitive ability (standardized), and α_a are cohort fixed effects. Since we use individual-level averages over 1998–2007, each individual contributes one observation. Standard errors, reported in parentheses throughout, are heteroskedasticity-robust. β captures the association between ability and income after absorbing cohort differences.

Table 2 presents results using both log and level specifications.

Table 2: Ability and Income: Log and Level Specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
	Logs		Logs, both outcomes > 0		Levels	
	Labor income	Capital income	Labor income	Capital income	Labor income	Capital income
Cognitive ability	0.209	0.649	0.178	0.639	5.633	1.176
	(0.001)	(0.003)	(0.001)	(0.003)	(0.019)	(0.052)
Beta/Mean					0.21	0.57
Obs	1,214,246	996,679	982,905	982,905	1,243,235	1,243,234
R^2	0.060	0.066	0.057	0.066	0.094	0.001
Mean	3.08	-1.78	3.14	-1.77	27.11	2.06

Estimates from $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. Dependent variable is average income over 1998–2007. Columns 1–4 use log income; columns 5–6 use levels in thousands of USD.

In the log specifications, a one standard deviation increase in cognitive ability is associated with 23 percent higher labor income ($\exp(0.209) - 1 = 0.23$) and 91 percent higher capital income ($\exp(0.649) - 1 = 0.91$). Log specifications are standard in the literature and provide a percentage interpretation, but they require excluding observations with zero or negative values (20% of the sample for capital income).[20]

In the level specifications (columns 5–6), the coefficient is larger for labor income ($5,633) than capital income ($1,176) in absolute terms, but normalizing by respective means yields a larger ratio for capital income ($\beta/\bar{Y}$ of 0.57 versus 0.21). Normalizing by standard deviations instead of means reverses the ranking, with standardized effects of 0.28 for labor income but only 0.03 for capital income, because the much greater dispersion of capital income compresses the standardized effect.

The log ratio of 3.1 partly reflects the heavy weight that the log specification places on near-zero observations, where capital income has substantial density.[21]

Two measurement issues suggest our capital income estimates are conservative. Our capital income measure excludes unrealized capital gains, which can be large during periods of rising asset prices. Since high-ability individuals hold more equity (as documented in Section 6) and equities appreciated substantially over our sample period, this omission likely *understates* the ability gradient in total capital income. Excluding most pension wealth works in the same direction: to the extent that high-ability individuals make better pension investment choices, both

[20]Under the broader capital income measure (including housing components), the coefficient is 0.328, roughly half the financial-only baseline (Appendix Table A1), consistent with the weaker ability gradient for housing-related components.

[21]Appendix Table A7 reports estimates using $\log(\text{income} + c)$ for constants c ranging from 0.25 to 1.00 times the sample mean. Both coefficients decline as c increases, but the capital coefficient remains larger at all shift values, so the ratio stays above one throughout (declining from 1.30 to 1.13).

omissions imply our capital income estimates are conservative. On the other hand, Sweden's compressed labor income distribution, a product of centralized wage bargaining, may attenuate the labor income coefficient relative to countries with greater wage dispersion.

4.3 Rank Regressions

A complementary approach converts both income measures to percentile ranks:

$$\text{Rank}(Y_{ia}) = \alpha_a + \beta \, Cog_i + \varepsilon_{ia}, \tag{4.2}$$

where $\text{Rank}(Y_{ia})$ is the percentile rank (0–100) of individual i's income. This approach includes all observations regardless of sign, expresses effects in comparable units (percentile points), and provides a distribution-free comparison. Table 3 presents the results.

Table 3: Rank Regressions: Ability and Income Percentile Rank.

	(1) Labor Income Rank	(2) Capital Income Rank (all)	(3) Capital Income Rank (pos. only)
Cognitive ability	9.579	7.285	6.890
	(0.024)	(0.025)	(0.028)
Observations	1,243,235	1,243,234	996,679
R^2	0.128	0.071	0.067

Dependent variable is percentile rank (0–100) of average income over 1998–2007. Column 1: labor income rank among all observations. Column 2: capital income rank including all observations. Column 3: capital income rank restricted to individuals with positive capital income. All specifications include birth cohort fixed effects.

A one standard deviation increase in cognitive ability is associated with moving up 9.6 percentile ranks in the labor income distribution and 7.3 percentile ranks in the capital income distribution. In rank terms, the ability gradient is stronger for labor income than for capital income, in contrast to the log-specification results. This reversal reflects how the two metrics weight different parts of the distribution. The log transformation amplifies variation near zero, where capital income has substantial density, widening the capital gradient relative to labor income. Ranks, by contrast, compress large absolute differences at the top of the distribution into small rank differences; since capital income is far more right-skewed than labor income, this compression disproportionately reduces the measured capital gradient. Ranks also include all observations regardless of sign, incorporating the 20% of individuals with non-positive capital income who are excluded from log specifications. Capital income rank is somewhat harder to interpret than labor income rank, as it reflects a combination of financial market participation, saving capacity, and labor income effects, rather than mapping onto a single dimension like occupational position. Nonetheless, the rank specification is valuable because it sidesteps the distributional issues that complicate log and level comparisons. When restricting to positive capital income (column 3), the coefficient declines to 6.9, indicating that the full-sample rank coefficient reflects both the extensive margin (whether one has positive capital income) and the intensive margin (ranking conditional on being positive).

4.4 Decomposing Extensive and Intensive Margins

The log specification for capital income combines the *extensive margin* (whether capital income is positive) and the *intensive margin* (how much, conditional on being positive). For labor income, nearly all observations are positive, so the coefficient primarily reflects intensive-margin variation. For capital income, with 20% non-positive observations, the extensive margin may contribute substantially. To quantify this, we implement a three-part decomposition. We partition observations into negative capital income (10%), zero (10%), and positive capital income (80%; see Table 1 and Appendix Table A6), then estimate ability's effect on each margin separately.

Table 4: Three-Part Decomposition: Extensive and Intensive Margins.

	Coefficient	Marginal effect
Panel A: Extensive margin		
Effect on $\Pr(CI > 0)$	0.053 (0.000)	+5.3 pp
Effect on $\Pr(CI < 0)$	−0.029 (0.000)	−2.9 pp
Panel B: Intensive margin		
$\log(CI) \mid CI > 0$	0.645 (0.003)	
$\log \lvert CI \rvert \mid CI < 0$	0.287 (0.007)	
Panel C: Decomposition		
Share from extensive margin	≈10%	
Share from intensive margin	≈90%	
Panel D: Matched-sample comparison		
β^{+}_{CI} (positive CI)	0.639	
β_{LI} (same individuals)	0.178	
Panel E: Chen & Roth imputation		
$\log(CI)$ with imputed zeros	0.749	

Panel A: Ordered logit for probability of being in negative/zero/positive capital income partition. Panel B: Log regressions estimated separately by sign. Panel C: Share of total effect from each margin. Panel D: Comparison of intensive-margin capital income coefficient to labor income coefficient on the matched sample (individuals with both outcomes positive, corresponding to Table 2 columns 3–4). Panel E: Imputation approach following Chen and Roth (2024). Since the treatment of zeros is inherently ambiguous, we compute two scenarios: one assigning zero-capital-income observations the minimum observed positive value, the other assigning the same magnitude as negative. The reported coefficient (0.749) is the average of the two scenarios.

Panel A shows that a one standard deviation increase in cognitive ability is associated with a 5.3 percentage point higher probability of having positive capital income and a 2.9 percentage point lower probability of negative capital income. Despite these sizable extensive-margin effects, Panel C indicates that approximately 90% of ability's total effect on expected capital income operates through the intensive margin.

Panel D compares the intensive-margin capital income coefficient (0.639) to the labor income coefficient on the matched sample (0.178), confirming that the large log gradient is not driven solely by extensive-margin selection. Panel E provides a complementary approach using the imputation method of Chen and Roth (2024), which assigns values to zero and negative observations rather than excluding them. The imputed coefficient (0.749) confirms that the large capital gradient is not an artifact of sample selection on positive values. Note that the log transformation amplifies heterogeneous effects more for capital income, which has much higher log-variance (Jensen's inequality; SD 2.69 versus 0.90 for labor income), so log-based comparisons will tend to yield larger capital gradients than level-based ones.[22]

Summary of Section 4. Table 5 collects the results across all approaches.

Table 5: Summary of Capital-to-Labor Ability Gradient Across Metrics.

Metric	Labor	Capital	Ratio (CI/LI)
Log coefficients	0.209	0.649	3.11
Log coefficients, matched sample	0.178	0.639	3.59
Chen & Roth imputation	0.209	0.749	3.58
Log-shift ($c = 0.50\bar{Y}$)	0.127	0.150	1.19
Rank (percentile points)	9.58	7.29	0.76
Level Beta/Mean	0.21	0.57	2.75
Standardized (Beta/SD)	0.28	0.03	0.10

Each row presents a different way of comparing ability's association with labor and capital income. The rank and standardized metrics include all observations; the log-based metrics restrict to positive values. No single metric is definitive; together they bracket the comparison.

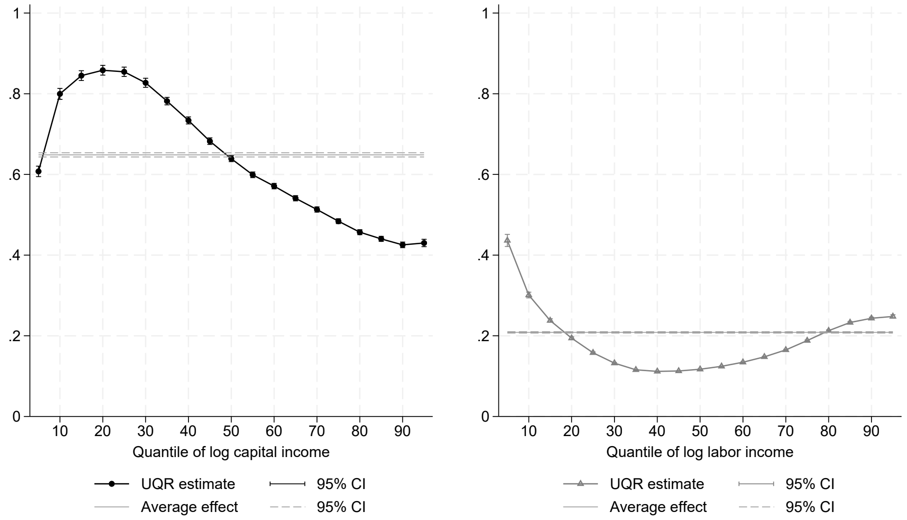
4.5 Associations Across the Distribution

Where in the distribution is ability's association with capital income most pronounced? Using the log specification, Figure 4 presents unconditional quantile regression estimates of β (Firpo et al., 2009) across vigintiles of the income distribution. The capital income coefficients exceed the labor income coefficients at nearly all quantiles, but the two curves have different shapes. For capital income, the gradient is hump-shaped, peaking around the 4th–6th vigintile before declining steadily. For labor income, the gradient is largest at the bottom, falls sharply toward

[22] See Appendix A.3 for details.

the median, and rises slightly at the top.[23]

Figure 4: Unconditional Quantile Regression Estimates.



Unconditional quantile regression estimates of β from $\log(Y_{ia}) = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. The y-axis shows the marginal effect of a one standard deviation increase in cognitive ability on log income at each vigintile. Horizontal lines show OLS estimates. Standard errors are bootstrapped with 500 repetitions.

As Table 5 makes clear, the comparison between ability's association with labor and capital income depends on the metric. What is robust, however, is that ability predicts capital income. The reduced-form coefficients cannot tell us why. Does ability predict capital income only indirectly, through higher labor income and hence more saving? Or does ability also shape saving behavior and investment returns directly?

5 Decomposing the Ability–Capital Income Link

To separate these channels, this section uses the decomposition framework from Section 2 together with detailed wealth register data on asset quantities, prices, and transactions. The analysis isolates two financial channels (saving and portfolio returns) through which ability may predict capital income beyond its association with labor income.

As described in Section 3, saving and return measures focus on financial assets only, excluding housing wealth and mortgage transactions. Appendix Table A22 provides descriptive

[23] The strong ability gradient at the bottom of the income distribution raises the question of who these low-income individuals with high ability gradients are. Examining observable characteristics, we find that individuals in the bottom quintile of labor income who have above-median cognitive ability tend to have below-median non-cognitive ability scores, suggesting these skills may compensate for each other in protecting against very low labor income.

statistics for the decomposition sample.

We estimate ability's direct effects on saving and returns by controlling for labor income:

$$\log S_{ia} = \alpha_{1a} + (1 + b_1) \log Z_{Lia} + m_1 \theta_i + \varepsilon_{ia}, \tag{5.1}$$

$$r_{ia} = \alpha_{2a} + b_2 \log Z_{Lia} + m_2 \theta_i + \varepsilon_{ia}. \tag{5.2}$$

The coefficients m_1 and m_2 capture direct effects of ability on saving and returns, independent of labor income.[24] Table 6 presents the results.

Table 6: Ability, Saving, and Portfolio Returns.

	(1)	(2)	(3)	(4)
	Panel A: Saving			
Cognitive ability	0.194 (0.002)	0.186 (0.025)	0.187 (0.002)	0.209 (0.002)
Log of labor income	1.104 (0.005)	1.170 (0.257)	1.128 (0.005)	-
Log of disposable income	-	-	-	1.200 (0.005)
Excl. saving ≤ 0	Yes	No	Yes	Yes
Excl. labor income $<$ \$15,000	Yes	Yes	Yes	No
Excl. saving $>$ 100% of disp. income	No	No	Yes	Yes
Obs	783,392	1,004,866	759,359	878,569
R^2	0.106	0.001	0.110	0.130
	(1)	(2)	(3)	(4)
	Panel B: Portfolio Return			
Cognitive ability $\times 100$	0.458 (0.045)	0.779 (0.021)	1.230 (0.022)	0.393 (0.044)
Log of labor income	-0.047 (0.117)	2.264 (0.069)	4.033 (0.071)	-
Log of disposable income	-	-	-	0.485 (0.125)
Conditional on having returns	Yes	No	No	Yes
Excl. labor income $<$ \$15,000	Yes	Yes	Yes	No
Obs	485,606	1,004,866	1,004,866	485,601
R^2	0.000	0.004	0.011	0.000

Panel A: dependent variable is saving. Columns 1, 3, 4 use logs; column 2 uses saving in levels, with the coefficient normalized by mean saving to obtain a semi-elasticity (following Thakral and Tô, 2023). Panel B: dependent variable is portfolio return. The coefficient is multiplied by 100 for percentage point interpretation. Column 1 conditions on having returns; columns 2–3 assign $r = -0.01$ and $r = -0.08$ to non-investors, following Chen and Roth (2024). All specifications include birth cohort fixed effects. The \$15,000 annual labor income threshold excludes individuals with very low earnings who are likely not fully attached to the labor market.

Saving. In our preferred specification (Panel A, column 1), a one standard deviation increase in cognitive ability is associated with 21 percent higher saving ($\exp(0.194) - 1 = 0.21$), conditional on labor income. The coefficient on log labor income is 1.1, implying a saving rate

[24] The coefficient on log labor income in the saving regression is $(1 + b_1)$ because $S = \Phi \cdot Z_L$, so $\log S = \log \Phi + \log Z_L$. The saving rate elasticity b_1 is therefore the estimated labor income coefficient minus one.

elasticity of $b_1 = 0.1$. At a baseline saving rate of 5 percent of disposable income, this translates to an increase of approximately 1 percentage point per standard deviation of ability.[25] These results are robust to alternative sample restrictions, to using non-parametric income controls with decile dummies (Appendix Table A23), and to excluding birth cohort fixed effects (Appendix Table A21).

Returns. Turning to returns, among investors a one standard deviation increase in ability predicts 0.46 percentage points higher annual returns (Panel B, column 1).[26] The coefficient increases markedly in columns 2–3, which assign $r = -0.01$ and $r = -0.08$ to non-investors.[27] Labor income has essentially no effect on returns conditional on ability (column 1). Column 4 uses disposable income instead of labor income and removes the $15,000 earnings threshold; the saving coefficient is slightly larger (0.209) while the return coefficient falls to 0.39 percentage points.

Unconditional versus Conditional Estimates. How much of the total ability-saving and ability-return relationships operate through higher labor income? Table 7 addresses this by comparing unconditional estimates (without income controls, columns 1–2) to the conditional estimates from Table 6 column 1 (reproduced in columns 3–4).

[25] Our estimates of the long-run elasticity of saving with respect to labor income are smaller than the estimates of Dynan et al. (2004), who find an elasticity of saving with respect to permanent income around 1. However, as a considerable amount of variation in labor income is driven by cognitive ability, the smaller conditional estimates here are expected.

[26] The portfolio return measure, defined in equation (3.2), is sensitive to extreme values. Appendix Section C.2 validates the measure against aggregate stock market returns and shows robustness to winsorizing and outlier exclusion.

[27] Column 1 conditions on having portfolio returns, excluding non-investors entirely. Following Chen and Roth (2024), columns 2–3 impute returns for non-investors to incorporate the extensive margin of financial market participation. The two imputed values bracket a range of opportunity costs of not investing; the large increase in the coefficient reflects the strong ability gradient in stock market participation documented in Section 6.

Table 7: Unconditional and Conditional Estimates: Ability, Saving, and Returns.

	(1)	(2)	(3)	(4)
	Unconditional		Conditional on Income	
	Log Saving	Portfolio Return (pp)	Log Saving	Portfolio Return (pp)
Cognitive ability	0.333	0.451	0.194	0.458
	(0.002)	(0.042)	(0.002)	(0.045)
Log of labor income	—	—	1.104	-0.047
			(0.005)	(0.117)
Observations	783,413	485,613	783,392	485,606
R^2	0.057	0.000	0.106	0.000
% reduction from unconditional	—		42%	−1%

Columns 1–2: unconditional estimates from $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. Columns 3–4: conditional estimates controlling for log labor income. Portfolio return coefficients are multiplied by 100 for percentage point interpretation. The bottom row shows the percentage reduction in the cognitive ability coefficient when controlling for income, indicating the share of the total association that operates indirectly through higher labor income.

For saving, the unconditional coefficient is 0.333 (column 1), and controlling for labor income reduces it by 42% to 0.194 (column 3). Roughly 42% of the total ability-saving relationship operates indirectly through higher labor income, while the remaining 58% represents direct effects of ability on saving behavior. For returns, the unconditional coefficient is 0.45 percentage points (column 2), and controlling for labor income does *not* reduce it; the conditional coefficient is slightly larger at 0.46 pp (column 4). Ability's association with investment performance is independent of labor income.

Quantitative accounting. How much of the gap between the log coefficients in Table 2 can be accounted for by the saving and return channels? Combining equation (2.3) with the estimated saving elasticity $b_1 = 0.1$ from Table 6, if ability affected capital income only indirectly through labor income (with no direct effects on saving or returns), we would expect a capital-to-labor coefficient ratio of approximately $1 + b_1 + b_2 \approx 1.1$ (since $b_2 \approx 0$; Table 6, Panel B). The observed ratio is approximately 3.1, implying direct effects $m_1 + m_2 = \beta_K - (1 + b_1 + b_2)\beta_L \approx 0.649 - 1.1 \times 0.209 \approx 0.42$ in log points.

A back-of-the-envelope calculation suggests these channels account for 60–70% of the excess. The saving coefficient $m_1 \approx 0.19$ implies that a one standard deviation increase in ability predicts approximately 19 log points higher capital income through higher saving rates alone. For returns, an additional 0.46 percentage points annually on a baseline return of roughly 5–7 percent translates to $m_2 \approx 0.07$–0.09 in log points. Together, $m_1 + m_2 \approx 0.26$–0.28. The remaining gap of approximately 0.14–0.16 log points likely reflects channels that our saving and return measures capture imperfectly: selection into asset classes with different return distributions, transaction timing within the year, ability-related differences in leverage and tax optimization, and the cumulative effect of saving and return differences over prior years of wealth accumulation. The residual likely reflects measurement error in both saving and returns, which would attenuate the estimated coefficients.[28]

The decomposition shows that ability's association with capital income operates through both saving and returns, but does not identify the specific financial behaviors driving these channels. We turn to this next.

6 Financial Behavior

This section examines the specific financial behaviors underlying the saving and return channels identified in Section 5.

6.1 Risk-Adjusted Returns

Higher returns could reflect superior stock selection (skill) or greater risk-taking.[29] We distinguish between skill and risk-taking using a two-factor model for stocks on the Stockholm Stock Exchange, computing individual alpha (risk-adjusted excess return) and beta (systematic risk).

Table 8: Ability and Excess Return and Risk.

	(1) Excess Return (α)	(2) Risk (β)
Cognitive ability	0.762 (0.088)	−0.006 (0.001)
Log of labor income	0.000 (0.114)	0.046 (0.001)
Mean	5.00	1.08
Obs	515,156	515,156
R^2	0.000	0.022

The effect on α is in annualized percentage points (converted from weekly estimates using $(1+r)^{52}-1$); the effect on β is in raw beta units (mean $\beta = 1.08$). Only individuals with Stockholm Stock Exchange stocks included.

Table 8 presents the results. A one standard deviation increase in ability is associated with 0.76 percentage points higher risk-adjusted returns (alpha) and approximately 0.6 percent *lower* systematic risk (beta). High-ability individuals thus achieve better performance while

[28] Analogous estimates for non-cognitive ability show weaker saving effects (coefficient 0.10 versus 0.19 for cognitive) and somewhat weaker return effects (Appendix Table A24).

[29] Dohmen et al. (2010) find a negative relationship between IQ and risk aversion, suggesting that individuals with high cognitive ability may prefer riskier assets and earn higher returns to compensate for increased risk. Appendix Figure A4 shows that financial professionals are drawn disproportionately from the upper tail of the cognitive ability distribution.

taking on less systematic risk, a pattern more consistent with investment skill than with risk compensation.[30]

In the terminology of the returns heterogeneity literature (Fagereng et al., 2020; Bach et al., 2020), these results are more consistent with "type dependence" (persistent individual-specific return differences reflecting skill) than with "scale dependence" (returns that increase mechanically with wealth), since the alpha effect survives conditioning on labor income.[31]

6.2 Portfolio Composition and Hand-to-Mouth Behavior

Table 9: Ability, Risky Asset Share, and Hand-to-Mouth Behavior.

	(1)	(2)	(3)	(4)
	Risky asset share		Hand-to-mouth	
	FW > 0	FW > 0 & RA > 0	Saving < 3%	Saving < 1.5%
Cognitive ability	2.555 (0.029)	-0.035 (0.030)	-2.856 (0.034)	-1.697 (0.026)
Log of labor income	2.631 (0.041)	-1.268 (0.043)	-1.784 (0.041)	-1.569 (0.034)
Mean, in percent	33.9	46.2	15.7	8.5
Obs	1,118,754	824,000	1,213,925	1,213,925
R^2	0.015	0.002	0.010	0.008

Effects in percentage points. FW = financial wealth, RA = risky assets. HTM defined as saving less than 3% (or 1.5%) of disposable income. Unlike the liquid asset-based definitions in Kaplan et al. (2014) and Aguiar et al. (2025), this consumption-based approach follows Kolsrud et al. (2020). See Kaplan et al. (2018) for the macroeconomic importance of HTM consumers.

Table 9 shows that cognitive ability strongly predicts holding risky assets (extensive margin) but has little association with the risky share conditional on participation (column 2). This suggests ability is primarily associated with the participation decision rather than portfolio allocation among participants (Appendix Figure A5 shows the gradients by stanine; Appendix Table A27 presents analogous results for non-cognitive ability). For hand-to-mouth (HTM) behavior, a one standard deviation increase in ability is associated with a 2.9 percentage point lower probability of HTM status. Individuals in the top 2.5 percent of ability have a substantially lower probability of being HTM than those in the bottom 2.5 percent.[32]

[30] The heterogeneity in risk-adjusted returns documented here also has implications for asset pricing. If a substantial fraction of equity market participants systematically earns below-market returns due to poor stock selection, the resulting transfer from low- to high-ability investors could contribute to the equity premium puzzle.

[31] For non-cognitive ability, a one standard deviation increase is also associated with higher excess returns (0.60 pp) but, unlike cognitive ability, with slightly higher rather than lower systematic risk (Appendix Table A25; see also Appendix Figure A3 for the full non-cognitive gradient profiles).

[32] Given the normal distribution of ability, two standard deviations above or below the mean correspond to the top or bottom 2.5 percent of the distribution. With a coefficient of 2.9 percentage points per SD, the top-to-bottom gap is approximately $4 \times 2.86 \approx 11.4$ percentage points.

Portfolio Diversification. Among individuals holding stocks directly (not through mutual funds), we examine whether cognitive ability predicts better diversification. Table 10 presents portfolio composition statistics by ability group. Measuring diversification requires matching individual holdings to unique securities using ISIN codes, which are available for approximately 50% of direct stock holdings; the unmatched holdings are predominantly shares in small non-public closely held corporations.

Table 10: Portfolio Composition by Cognitive Ability Group.

	1 (Low)	2	3	4	5 (High)
Panel A: Ownership Rates (%)					
Any financial assets	82.46	89.38	92.34	94.39	96.51
Direct stockholding	27.15	36.07	42.24	48.73	56.65
Mutual funds (equity)	41.26	49.89	54.92	59.24	64.33
Panel B: Diversification (direct stockholders)					
Mean number of stocks held	4.24	4.80	5.30	5.84	6.57
% holding only 1 stock	80.50	72.10	65.75	59.26	50.92
Panel C: Portfolio Returns (conditional on ownership)					
Mean portfolio return (%)	6.95	7.61	8.11	8.49	8.33
Median portfolio return (%)	3.33	5.40	6.38	7.27	7.36
Std. dev. of returns (%)	10.03	10.99	8.60	9.05	6.74
Observations (full sample)	260,186	188,876	273,720	211,536	308,952

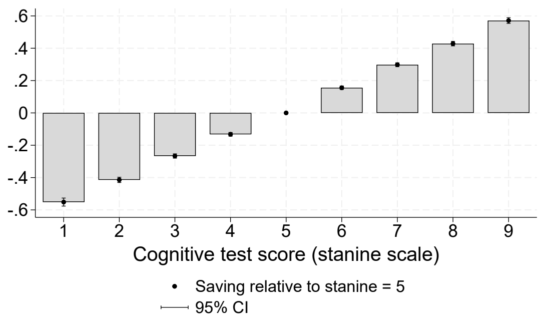
Cognitive ability groups defined by stanine score: group 1 (stanines 1–3), group 2 (stanine 4), group 3 (stanine 5), group 4 (stanine 6), group 5 (stanines 7–9). Panel A shows ownership rates; Panel B is restricted to direct stockholders; Panel C is restricted to individuals with non-zero portfolio returns. Note: Diversification measures in Panel B require matching individual holdings to unique securities using ISIN codes, which is available for approximately 50% of direct stock holdings. Results should be interpreted with this data limitation in mind.

Panel A shows large ability gradients in financial market participation: ownership of any financial assets rises from 82% in the lowest ability group to 97% in the highest, and direct stockholding rises from 27% to 57%. High-ability investors also hold more stocks and are less likely to hold undiversified single-stock portfolios (Panel B), consistent with ability operating through better-informed participation and selection rather than greater risk-taking. Panel C shows that median portfolio returns increase monotonically with ability (from 3.3% to 7.4%), though mean returns are non-monotonic (group 4: 8.49%, group 5: 8.33%). The highest-ability group exhibits the lowest return volatility (standard deviation of 6.7%), though the pattern across groups is not monotonic.

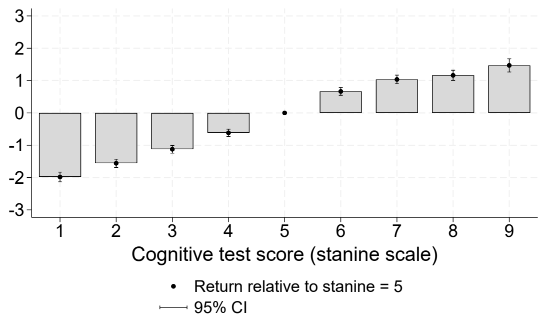
6.3 Ability Gradients

Figure 5 shows ability gradients using stanine dummies. The saving gradient (Panel A) is roughly symmetric in log points: individuals at stanine 9 save approximately 0.6 log points more than those at the median, while those at stanine 1 save approximately 0.5 log points less. The return gradient (Panel B) shows a top-to-bottom gap of approximately 3.5 percentage points, with the gradient steeper below the median. The excess return gradient (Panel C) is broadly consistent with superior investment selection rather than risk compensation: alpha is higher for high-ability individuals, though the pattern is non-monotonic at the bottom of the ability distribution (the small stanine 1 group has imprecisely estimated positive alpha). Portfolio risk (Panel D) is lower for high-ability investors.

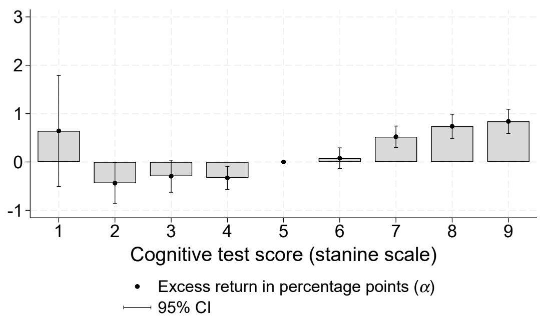
Figure 5: Ability Gradients in Financial Behavior.



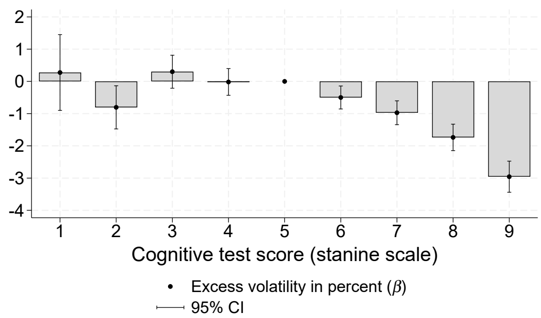
Panel A: Saving



Panel B: Rate of return



Panel C: Excess return



Panel D: Portfolio risk

Coefficients from regressions with stanine dummies (1–9), reference category = 5. We use stanines rather than quintiles because this is the native scale of the Swedish military cognitive assessment, avoiding arbitrary binning decisions. Results are qualitatively similar using quintiles or deciles.

In sum, cognitive ability predicts participation in financial markets, better-diversified portfolios, lower hand-to-mouth rates, and, conditional on participation, higher risk-adjusted returns with lower systematic risk. These patterns are consistent with the saving and return channels documented in Section 5.

7 Robustness and Extensions

The decomposition in Sections 5–6 rests on the ability–income associations established in Section 4. This section examines the robustness of those associations to alternative controls, specifications, and sample definitions. Appendix tables report both log and rank specifications; the text focuses on logs but notes where rank results differ materially.

Education and Occupation Controls. Controlling for education and occupation reduces both labor and capital income coefficients, but the labor coefficient declines proportionally more.[33] With both sets of controls, the labor coefficient falls by 59 percent (from 0.178 to 0.073) while the capital coefficient falls by 54 percent (from 0.639 to 0.292). The residual capital coefficient remains four times larger than the residual labor coefficient in the log specification. In ranks, education and occupation reduce the labor gradient proportionally more (66 percent) than the capital gradient (53 percent), but the residual coefficients are similar in magnitude (3.4 versus 3.3 percentile ranks), consistent with the metric sensitivity documented in Section 4 (Appendix Table A11).

Family Background. Controlling for parental labor income slightly reduces the labor income coefficient, as expected if children of high-income parents use social connections to access high-wage jobs (see, e.g., Plug et al., 2018), but has little effect on the capital income coefficient. Sibling fixed effects reduce the capital coefficient by 45 percent and the labor coefficient by 22 percent.[34] However, sizable ability effects persist. Rank specifications show a similar pattern, with sibling fixed effects reducing the capital gradient by 52 percent and the labor gradient by 21 percent. Bequests have modest effects in both metrics (Appendix Table A12).

Non-Cognitive Ability and Height. Non-cognitive ability (Heckman et al., 2006; Lindqvist and Vestman, 2011; Lundberg, 2017) and height (Schultz, 2002; Case and Paxson, 2008; Schick and Steckel, 2015; Lindqvist, 2012; Lundborg et al., 2014) also predict higher income in both markets, but the capital-to-labor ratio of log coefficients is smaller for both than for cognitive ability (non-cognitive ratio 2.4, height ratio 2.9, compared to 3.2 for cognitive ability in the

[33] Dahl et al. (2023) examines the impact of college majors on labor earnings. In capital markets, education and work experience also shape saving behavior and asset returns through mechanisms such as financial literacy (see, e.g., Agarwal and Mazumder, 2013; Lusardi and Mitchell, 2014; Lusardi et al., 2017; Altmejd et al., 2024).

[34] A large body of empirical evidence documents the intergenerational transmission of income and wealth, including studies using Swedish data by Björklund and Jäntti (1997), Björklund et al. (2012), and Adermon et al. (2018). One explanatory factor is partial inheritance of abilities; Grönqvist et al. (2017) estimate a father-son correlation in cognitive ability of 0.32 to 0.35.

bivariate specification). In rank specifications, the capital gradient is smaller than the labor gradient for all three measures, but cognitive ability retains the highest capital-to-labor ratio (0.79, versus 0.66 for non-cognitive and 0.77 for height). When all three measures are included simultaneously, cognitive ability remains the strongest predictor of capital income in both log and rank specifications (Appendix Table A10, Panels B and D). A caveat is that the two ability measures differ in psychometric properties: cognitive ability is machine-scored, while non-cognitive ability relies on a psychologist's evaluation. Differential measurement error could attenuate the non-cognitive coefficients.

Gender and Alternative Ability Measures. A limitation of military enlistment data is that it covers only men. As a robustness check and to extend the analysis to women, we use high school GPA as an alternative ability measure available for both genders. The capital gradient exceeds the labor gradient for both men and women in both log and rank specifications, and the qualitative findings are similar across genders (Table 11).

Table 11: Ability Gradients Using GPA and Math Grades.

Panel A: GPA (logs)	(1)	(2)	(3)	(4)
	Men		Women	
	LI	CI	LI	CI
GPA	0.150 (0.001)	0.561 (0.003)	0.156 (0.001)	0.590 (0.003)
Obs	832,803	700,562	787,055	677,187
R^2	0.062	0.063	0.064	0.062
Panel B: Math Grades (logs)				
	Men		Women	
	LI	CI	LI	CI
Math	0.106 (0.001)	0.497 (0.005)	0.135 (0.002)	0.493 (0.005)
Obs	285,021	241,292	272,808	237,767
R^2	0.055	0.052	0.043	0.045
Panel C: GPA (ranks)				
	Men		Women	
	LI	CI	LI	CI
GPA	2.991 (0.019)	6.690 (0.032)	3.275 (0.019)	6.667 (0.031)
Obs	845,681	845,831	802,154	802,727
R^2	0.055	0.058	0.083	0.065
Panel D: Math Grades (ranks)				
	Men		Women	
	LI	CI	LI	CI
Math	2.259 (0.030)	5.929 (0.053)	2.878 (0.031)	5.953 (0.052)
Obs	288,699	288,732	278,603	278,800
R^2	0.055	0.044	0.046	0.048

Sample in Panels A, C: born 1955–1975; Panels B, D: born 1967–1975. LI = Labor Income, CI = Capital Income. CI uses the financial capital income measure (dividends + interest + net capital gains). Panels A–B use log specifications on the positive-income sample; Panels C–D use rank specifications (percentile rank 0–100) on the unrestricted sample.

Sample Restrictions. Excluding observations in the top and bottom 1 percent of the income distributions yields qualitatively similar results (Appendix Table A14). Results are also robust to flexible controls for age at test in months (Appendix Table A15).

Taxation and Income Shifting. A potential concern is that high-ability individuals reclassify labor compensation as capital income to exploit lower capital tax rates (Bastani and Waldenström, 2021). Excluding owners of closely-held corporations, the primary vehicle for such shifting in Sweden, leaves estimates virtually unchanged (capital coefficient 0.646 versus 0.644 baseline); the same holds when additionally excluding unincorporated business owners (coefficient 0.660). Rank specifications are equally stable (Appendix Table A13). Our mechanism analysis in Sections 5–6 measures saving behavior and portfolio returns directly from wealth records, independent of how income is classified. The finding that high-ability individuals earn higher risk-adjusted excess returns (Table 8) cannot reflect income relabeling.

Sweden's dual income tax (progressive on labor, proportional on capital) substantially compresses the log labor coefficient while the log capital coefficient is unchanged (Appendix Tables A16 and A17). Total taxes paid are still progressive, but the proportional capital tax preserves the capital income gradient while progressivity substantially reduces the labor gradient. The tax system thus amplifies the *relative* ability differential between markets.

Lifecycle Patterns. The ability gradient is present across all age groups. Prior research shows labor market returns to ability increase with experience (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Falch and Sandgren Massih, 2012). Our sample spans birth cohorts 1951–1975 observed during 1998–2007, creating variation in age at observation. While we cannot follow individuals over a longer period of time, comparing cohorts observed at different ages is informative. As shown in Appendix Figure A2, the ability gradient is present for both young and old cohorts, with income dispersion increasing for older cohorts. Defining income ranks within birth cohorts rather than across the full sample yields nearly identical patterns (Appendix Figure A1). Detailed results by age group appear in Appendix Tables A18 and A19. To partially disentangle age from cohort effects, we also compare the same cohorts across two sub-periods (1998–2002 and 2003–2007). The results (Appendix Table A20) reveal employer learning in labor markets (young cohorts' labor coefficient increases by 39% between periods) while capital income coefficients remain relatively stable. Rank specifications confirm the same dynamic: the young cohort's labor rank gradient increases by 30% between periods while the capital rank gradient is flat. Edin et al. (2022) document declining returns to cognitive ability over recent decades in Sweden, suggesting that our estimates may differ for more recent cohorts.

8 Conclusion

This paper bridges two literatures: one studying the link between cognitive ability and labor market performance, and one studying how ability shapes financial behavior. By examining both markets for the same individuals using the same ability measure, we document three results. First, cognitive ability predicts capital income. The comparison with labor income is metric-sensitive: in log specifications the capital gradient is larger, while rank-based comparisons using the enlistment measure show similar or smaller gradients. Second, the capital-income gradient is only partially explained by labor income: a decomposition shows that ability is associated with higher saving rates and investment returns through channels beyond labor income. These channels can account for the majority of the excess of the observed gradient over what labor income effects alone would predict. Third, the investment return channel is consistent with skill rather than risk compensation, as high-ability individuals earn higher risk-adjusted excess returns while holding portfolios with lower systematic risk. The ability–income associations are not fully explained by education, occupation, or family background, and cannot be attributed to income shifting between tax bases. Using high school GPA as an alternative ability measure available for both genders, we find similar patterns for women. A lifecycle analysis suggests that labor income returns increase with experience while capital income returns are relatively stable across age groups.

These findings are relevant for understanding inequality and for tax and pension policy design. If ability is associated with capital income through channels beyond labor income, wealth inequality related to cognitive ability may be larger than labor-income-based measures alone would suggest. The persistent associations after controlling for education and parental background suggest that the link between cognitive ability and capital income is not fully accounted for by standard human capital measures. For optimal taxation, the Mirrleesian framework ties tax schedules to the ability-earnings relationship, treating the labor market as the primary arena in which ability generates income differences. If ability is associated with capital accumulation and portfolio returns in ways not fully captured by the labor-earnings relationship, this raises questions about the relative tax treatment of labor and capital income. Our findings show that Sweden's dual tax system –progressive on labor, proportional on capital – amplifies rather than offsets the differential.

Several caveats apply. Our estimates are conditional correlations; cognitive ability may proxy for risk preferences, discount rates, or family financial sophistication that independently affect financial behavior. Although Swedish tax data report capital income and wealth at the individual level (not the household level), we cannot fully account for household-level financial decisions (e.g., how couples jointly allocate portfolios or divide saving responsibilities), since investment choices may be coordinated within households. If accumulated capital income partly reflects permanent income better than current earnings do, the capital income coefficient could to some extent reflect permanent income rather than financial behavior; however, our use of ten-year averages for both income types substantially reduces this concern. Sorting of high-ability individuals into firms that offer superior pension plans or other employer-sponsored saving vehicles could also contribute to the observed gradient, though our occupation controls partially address this channel. The 1998–2007 sample period, characterized by generally rising asset prices, underscores the need for longer-term studies spanning complete market cycles. Sweden's compressed labor income distribution may attenuate the labor income gradient relative to countries with greater wage dispersion, and our exclusion of unrealized gains and pension wealth may understate the capital income gradient. Despite these limitations, the evidence consistently indicates that cognitive ability is associated with saving behavior, investment performance, and portfolio outcomes through channels not captured by labor income alone.

Evidence from Finland (Grinblatt et al., 2011), the United States (Barth et al., 2020), and European household surveys (Christelis et al., 2010) suggests these patterns extend beyond Sweden, though magnitudes may differ. The ongoing shift from defined benefit to defined contribution pension systems in many countries increases the stakes.[35] As more retirement wealth depends on individual investment decisions, differences in portfolio returns associated with ability will translate more directly into retirement income inequality. Investigating how financial education, default pension design, and investment product regulation shape the channels linking ability to capital market outcomes is a natural next step.[36]

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[35] In Sweden, the public premium pension system allocates 2.5 percent of earned income to individual accounts, with several hundred funds to choose from; individuals who make no active choice are assigned a professionally managed default fund. Similar individual-account systems include 401(k) plans in the United States and self-invested personal pensions in the United Kingdom.

[36] To the extent that technological change favors higher cognitive ability (Autor, 2015; Acemoglu and Restrepo, 2018; Agrawal et al., 2019), the capital market mechanisms documented here may gain importance, though Edin et al. (2022) find declining labor market returns to cognitive ability in Sweden in recent decades.

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Online Appendix

Cognitive Ability in Labor and Capital Markets

A Additional Results and Robustness Checks

Most tables present both log and rank specifications. A few tables use log specifications only.

A.1 Different Components of Capital Income

Table A1: Ability Gradients Across Components of Capital Income.

	(1) Broad cap. inc.	(2) Interest income	(3) Dividend income	(4) Realized cap. gain	(5) Realized cap. loss	(6) Debt interest payment	(7) Imputed rents
Cognitive ability	0.328	0.365	0.579	0.457	0.250	0.182	0.226
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
Obs	878,574	958,713	901,271	800,141	564,932	1,195,630	965,154
R^2	0.083	0.048	0.055	0.052	0.016	0.028	0.079

Beta-coefficients from $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$. Each column uses the log of the respective component as the dependent variable, restricting to positive values. The positive coefficients on capital losses (column 5) and debt interest (column 6) indicate that high-ability individuals realize larger losses and pay more debt interest, consistent with more active financial market participation and greater use of leverage, not poorer financial performance.

A.2 Sample Restrictions and Figure Trimming

Table A2 shows how the sample size changes under the trimming rules applied in the income distribution figures (Figure 1). For labor income, very few observations are excluded; for capital income, the trims remove the tails of a highly dispersed distribution while retaining the vast majority of observations.

Table A2: Effect of Sample Restrictions on the Distribution Figures.

Restriction	N	% of full sample
Labor income		
Full sample (all with LI data)	1,243,235	100.0
Excluding LI = 0	1,213,925	97.6
Additionally excluding LI > \$87,000	1,201,519	96.6
Capital income		
Full sample (all with CI data)	1,243,231	100.0
Excluding CI < −\$6,000	1,217,123	97.9
Additionally excluding CI > \$10,000	1,177,340	94.7

Restrictions applied separately to each panel of Figure 1. The trimming removes extreme tails to improve visual clarity; all regression analyses use the full (untrimmed) samples as reported in each table.

A.3 Three-Part Decomposition: Methodology

This section provides methodological details for the three-part decomposition presented in Table 4 of the main text. The capital income distribution poses distinctive challenges: approximately 20% of observations have non-positive values (primarily from net capital losses exceeding dividend and interest income), and positive values are highly right-skewed. Standard log specifications necessarily exclude negative and zero observations, while level specifications are dominated by extreme values. The three-part decomposition addresses this by partitioning observations and estimating ability's effect on each margin separately.

Step 1: Extensive Margin. We estimate an ordered logistic regression for the probability of being in each partition:

$$\Pr(CI_i \in \{<0, =0, >0\}) = f(\alpha + \delta \cdot Cog_i + \gamma_a), \tag{A.1}$$

where the ordered logit assumes an underlying latent variable. This captures how ability shifts the probability distribution across the three regions.

Step 2: Intensive Margins. We estimate separate regressions for the magnitude conditional on sign:

$$\log(CI_i) = \alpha^+ + \beta^+ \cdot Cog_i + \gamma_a + \varepsilon_i \quad \text{if } CI_i > 0 \tag{A.2}$$

$$\log|CI_i| = \alpha^- + \beta^- \cdot Cog_i + \gamma_a + \varepsilon_i \quad \text{if } CI_i < 0 \tag{A.3}$$

Here β^+ captures ability's effect on log capital income among those with positive income, while β^- captures ability's effect on the log magnitude of losses among those with negative income.

Step 3: Combined Effect. Using the law of total expectation, the total marginal effect of a one standard deviation increase in cognitive ability on expected capital income can be decomposed:

$$\frac{\partial E[CI]}{\partial Cog} = \underbrace{\frac{\partial \Pr(CI>0)}{\partial Cog} \cdot E[CI|CI>0] + \Pr(CI>0) \cdot \frac{\partial E[CI|CI>0]}{\partial Cog}}_{\text{Contribution from positive CI}}$$
$$- \underbrace{\frac{\partial \Pr(CI<0)}{\partial Cog} \cdot E[|CI||CI<0] + \Pr(CI<0) \cdot \frac{\partial E[|CI||CI<0]}{\partial Cog}}_{\text{Contribution from negative CI}} \tag{A.4}$$

The negative sign before the second term reflects that $E[CI \mid CI < 0]$ is negative; the absolute value notation in the equation ensures positive quantities, and the leading minus sign restores the correct sign.

We calculate the semi-elasticity, $\beta_{CI} = \frac{\partial E[CI]}{\partial Cog} \cdot \frac{1}{E[CI]}$, as:

$$\beta_{CI} = \underbrace{\left(\frac{\partial \Pr(CI>0)}{\partial Cog} + \Pr(CI>0) \cdot \beta^{+}_{CI}\right) \cdot \frac{E[CI|CI>0]}{E[CI]}}_{\text{Contribution from positive CI}}$$
$$- \underbrace{\left(\frac{\partial \Pr(CI<0)}{\partial Cog} + \Pr(CI<0) \cdot \beta^{-}_{CI}\right) \cdot \frac{E[|CI||CI<0]}{E[CI]}}_{\text{Contribution from negative CI}} \tag{A.5}$$

Here $\beta^{+}_{CI} \equiv \frac{\partial E[CI|CI>0]}{\partial Cog} / E[CI \mid CI > 0]$ denotes the level semi-elasticity (0.502 in Table A3), which differs from the log coefficient β^{+} in Step 2 (0.645) due to Jensen's inequality; similarly for β^{-}_{CI}.

Step 4: Computation of semi-elasticities. To compute the semi-elasticity in equation (A.5) we use estimates from Table 4 and Table A3. We begin by calculating β_{CI} in levels, and then we use the approximation

$$\beta_{CI} = \frac{\partial E[CI]}{\partial Cog} \cdot \frac{1}{E[CI]} \approx \frac{\partial \log |CI|}{\partial Cog}. \tag{A.6}$$

The approximation holds with equality when capital income is log-normally distributed, which it is not. The gap between the two sides reflects Jensen's inequality: the level-based semi-elasticity $(\partial E[CI]/\partial Cog)/E[CI]$ measures the percentage change in *average* capital income from a one standard deviation increase in cognitive ability, while the log estimate $\partial \log CI/\partial Cog$ measures the *average percentage change* across individuals.

Each statistic in Table A3 is computed for four subsamples, $\mathcal{S}_k$, with $k \in \{1, 2, 3, 4\}$. $\mathcal{S}_1$

contains observations with $CI > 0$ and $\mathcal{S}_2$ those with $CI < 0$. Combining $\mathcal{S}_1$ and $\mathcal{S}_2$ excludes observations with zero capital income. To include them, we construct two additional samples: $\mathcal{S}_3$ with $CI \geq 0$ and $\mathcal{S}_4$ with $CI \leq 0$. To estimate effects on log capital income for samples that include zeros, we impute values following Chen and Roth (2024). We normalize capital income by its minimum positive value and replace $\log(CI = 0)$ with 0, so that a move across the extensive margin is valued at the minimum of capital income. As a robustness check, we also impute zeros with $-x$ for $x \in \{0.5, 1, 2\}$, assigning greater weight to extensive-margin responses. These estimates appear in Table A5, which also reports analogous imputations for labor income. The log estimates including imputed zeros are larger than those excluding zeros, as seen in columns 3 and 4 of Table A3.

Table A3: Inputs for Semi-Elasticity Computation.

	$\mathcal{S}_1$ $(CI > 0)$	$\mathcal{S}_2$ $(CI < 0)$	$\mathcal{S}_3$ $(CI \geq 0)$	$\mathcal{S}_4$ $(CI \leq 0)$
$E[CI \mid \mathcal{S}_k]$	2.63	−0.49	2.34	−0.25
$E[LI \mid \mathcal{S}_k]$	27.37	25.12	25.88	19.49
$\Pr(\mathcal{S}_k)$	0.80	0.10	0.90	0.20
$\frac{\partial \Pr(\mathcal{S}_k)}{\partial Cog}$	0.053 (0.0003)	−0.029 (0.0002)	0.006 (0.0002)	−0.060 (0.0004)
$\frac{\partial \log \lvert CI \rvert}{\partial Cog}$	0.645 (0.003)	0.287 (0.007)	1.455 (0.005)	1.612 (0.011)
$\frac{\partial \lvert CI \rvert}{\partial Cog}$	1.320 (0.064)	−0.110 (0.011)	1.291 (0.057)	−0.113 (0.006)
$\frac{\partial \lvert CI \rvert}{\partial Cog} \cdot \frac{1}{E[\lvert CI \rvert \mid \mathcal{S}_k]}$	0.502	−0.224	0.552	−0.452

Each column corresponds to a subsample defined by the sign of capital income. $\mathcal{S}_1$: positive CI. $\mathcal{S}_2$: negative CI. $\mathcal{S}_3$: non-negative CI (includes zeros). $\mathcal{S}_4$: non-positive CI (includes zeros). Conditional means in thousands of USD. Standard errors in parentheses. All regressions include birth cohort fixed effects.

Using the estimates in Table A3, we calculate semi-elasticities for the effect of cognitive ability on capital income using both level and log estimates. The four subsamples can be combined in three ways to cover the full population. The first three columns of Table A4 show calculations for each combination, while column 4 reports the mean across all three.

Table A4: Semi-Elasticities of Capital Income with Respect to Cognitive Ability.

Subsample combination	(1) $\mathcal{S}_1 \cup \mathcal{S}_2$	(2) $\mathcal{S}_1 \cup \mathcal{S}_4$	(3) $\mathcal{S}_2 \cup \mathcal{S}_3$	(4) Mean
β_{CI} (from levels)	0.585	0.580	0.576	0.580
β_{CI} (from logs)	0.727	0.695	1.494	0.972

Semi-elasticities computed using equation (A.5) and the inputs in Table A3. Each column uses a different combination of subsamples to cover the full population. Column 1 combines $\mathcal{S}_1$ $(CI > 0)$ and $\mathcal{S}_2$ $(CI < 0)$, excluding zeros. Column 2 combines $\mathcal{S}_1$ and $\mathcal{S}_4$ $(CI \leq 0)$. Column 3 combines $\mathcal{S}_2$ and $\mathcal{S}_3$ $(CI \geq 0)$. Column 4 is the mean across the three combinations.

The level-based semi-elasticities are stable across all three combinations (0.576–0.585). The log-based estimates are more sensitive to the treatment of zeros: column 3 is substantially larger because $\mathcal{S}_3$ includes imputed values for all zero-CI observations, amplifying the extensive-margin gradient. We report the simple mean in column 4.

We can now compute the β_{CI}/β_{LI} ratios using the average estimates from column 4 in Table A4. For the level-based semi-elasticity, $\beta_{LI} = 0.21$ (Table 5); for the log-based semi-elasticity, $\beta_{LI} = 0.32$, computed by applying the same subsample-combination approach to labor income.[37] This gives ratios of $\beta_{CI}/\beta_{LI} = 0.58/0.21 = 2.8$ for levels and $\beta_{CI}/\beta_{LI} = 0.97/0.32 = 3.0$ for logs.

The consistency of the level-based ratio (2.8) with the Beta/Mean ratio (2.75) from Table 5 and the log-based ratio (3.0) with the main log-coefficient ratio confirms that the three-part decomposition provides a coherent accounting of the full-sample effect.

Table A5 reports the sensitivity of the log estimates to the imputation of zeros, following Chen and Roth (2024). We normalize capital income by its minimum positive value, replace zeros with 0 (baseline) or with $-x$ for $x \in \{0.5, 1, 2\}$. Larger values of x assign greater weight to extensive-margin responses.

[37] For $\mathcal{S}_1 \cup \mathcal{S}_2$ (excluding zeros), we use the standard log coefficient on positive labor income (0.209); for the two combinations including imputed zeros ($\mathcal{S}_1 \cup \mathcal{S}_4$ and $\mathcal{S}_2 \cup \mathcal{S}_3$), we use the full-sample imputed coefficient (0.381, Table A5 Panel A). The mean across all three combinations is $(0.209 + 0.381 + 0.381)/3 = 0.32$.

Table A5: Sensitivity of Log Estimates to Imputation of Zeros.

	$x = 0$	$x = 0.5$	$x = 1$	$x = 2$
Panel A: Labor Income (full sample)				
Cognitive ability	0.381	0.390	0.399	0.417
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	1,243,235	1,243,235	1,243,235	1,243,235
R^2	0.035	0.034	0.034	0.032
Panel B: Capital Income, $\mathcal{S}_3$ ($CI \geq 0$)				
Cognitive ability	1.455	1.485	1.516	1.577
	(0.005)	(0.005)	(0.005)	(0.006)
Observations	1,118,434	1,118,434	1,118,434	1,118,434
R^2	0.079	0.078	0.077	0.076
Panel C: Capital Income, $\mathcal{S}_4$ ($CI \leq 0$)				
Cognitive ability	1.619	1.556	1.494	1.369
	(0.011)	(0.011)	(0.011)	(0.010)
Observations	247,730	247,730	247,730	247,730
R^2	0.077	0.077	0.077	0.077

Log regressions with imputed values for zeros. The baseline ($x = 0$) replaces $\log(CI = 0)$ with 0 after normalizing by the minimum positive value; $x > 0$ replaces zeros with $-x$, assigning greater weight to extensive-margin responses. Panel A: labor income (all observations, including those with zero labor income). Panel B: capital income for $\mathcal{S}_3$ (non-negative CI). Panel C: capital income for $\mathcal{S}_4$ (non-positive CI). All regressions include birth cohort fixed effects. Robust standard errors in parentheses.

A.4 Characteristics by Capital Income Sign

Who has non-positive financial capital income? Table A6 compares observable characteristics across the three capital income groups (positive, zero, and negative). This comparison clarifies the extent to which selection into positive capital income is related to ability versus other observable factors.

Table A6: Observable Characteristics by Capital Income Sign.

	CI > 0	CI = 0	CI < 0
N	995,501	122,933	124,797
Mean labor income (1000 USD)	28.78	14.32	26.30
	(16.80)	(11.08)	(20.41)
Mean years of education	12.64	11.47	12.46
	(2.07)	(1.86)	(1.93)
Mean age	39.88	39.86	38.50
	(7.27)	(7.16)	(6.86)
% married	47.53	27.27	43.73
% foreign born	1.72	6.48	2.06
% employed	77.44	60.29	76.73
% self-employed	12.87	4.41	10.33
% unemployed	5.58	15.19	8.07
% not in labor force	4.12	20.11	4.88
% left sample by 2007	1.43	5.82	1.60
Share of full sample (%)	80.07	9.89	10.04

Financial capital income = dividends + interest + net realized capital gains. Groups defined by sign of individual-level average capital income over 1998–2007. Standard deviations in parentheses. Marriage rate, education level, and labor force status measured in 2007. "Left sample" reflects death or outmigration by 2007. The zero-capital-income group is most distinctive: higher unemployment, more individuals outside the labor force, more foreign-born, and fewer married.

A.5 Sensitivity to Log Transformation

Table A7: Sensitivity to Log Transformation: log(Income + c).

	(1) $c = 0.25\bar{Y}$	(2) $c = 0.50\bar{Y}$	(3) $c = 0.75\bar{Y}$	(4) $c = 1.00\bar{Y}$
Panel A: Labor Income				
Cognitive ability	0.158	0.127	0.107	0.093
	(0.001)	(0.000)	(0.000)	(0.000)
Observations	1,243,235	1,243,235	1,243,235	1,243,235
Panel B: Capital Income				
Cognitive ability	0.206	0.150	0.123	0.105
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,219,235	1,231,566	1,235,981	1,238,201
Ratio (B/A)	1.30	1.19	1.15	1.13

Estimates of $\log(Y_{ia} + c) = \alpha_a + \beta Cog_i + \varepsilon_{ia}$, where c is a fraction of the respective income mean $\bar{Y}$. Adding constants allows inclusion of zero and negative values and reduces the influence of near-zero observations. Both coefficients decline as c increases. The capital coefficient remains larger than the labor coefficient at all shift values, so the ratio stays above one throughout but declines toward one (from 1.30 to 1.13), confirming that the large log ratio (3.11) is partly amplified by the concentration of capital income near zero.

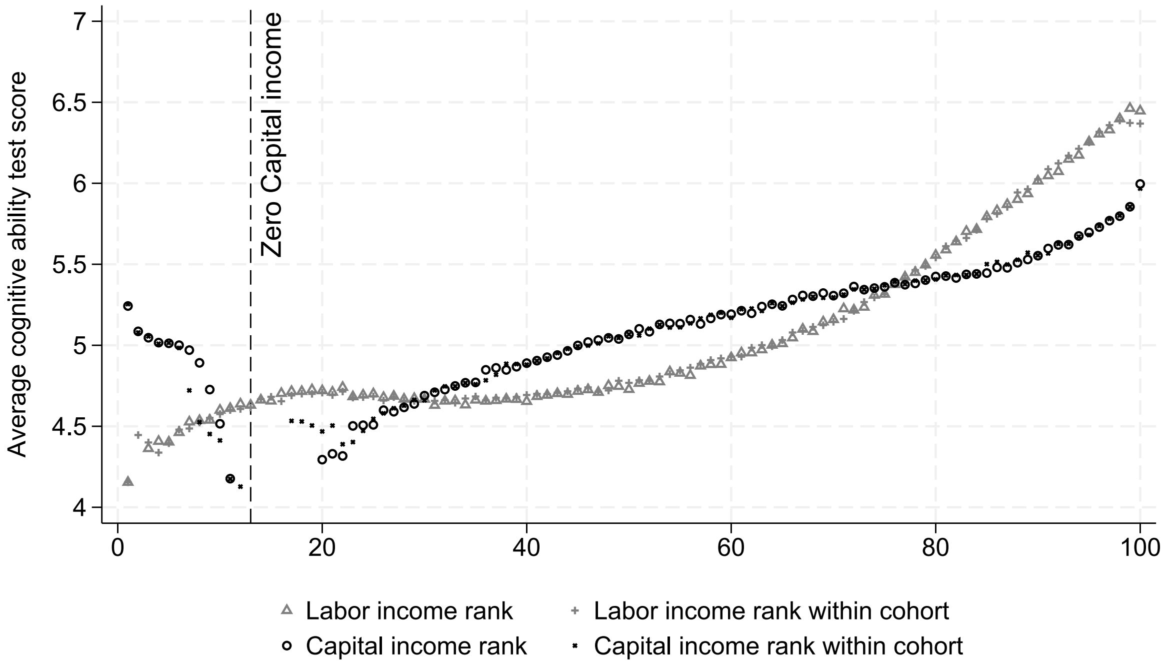
A.6 Within-Cohort Standardization

Table A8: Log Specifications with Within-Cohort Standardized Ability.

	(1)	(2)	(3)	(4)
	Full-Sample Std.		Within-Cohort Std.	
	Labor Income	Capital Income	Labor Income	Capital Income
Cognitive ability	0.208	0.648	0.177	0.639
	(0.001)	(0.003)	(0.001)	(0.003)
Observations	1,213,925	996,679	982,640	982,640
Ratio (CI/LI)	3.12		3.61	

Within-cohort standardization removes cohort-level differences including Flynn effect. Columns 1–2 use full-sample standardization on each income's positive sample; columns 3–4 use within-cohort standardization on the matched sample (both incomes positive). The within-cohort ratio (3.61) is higher than the full-sample ratio (3.12) because the matched sample excludes individuals with non-positive capital income.

Figure A1: Cognitive Ability Along the Income Distribution: Within-Cohort Ranks.



Average cognitive test scores across within-cohort income percentiles. Income ranks are defined separately within each birth cohort to account for lifecycle differences in income levels. Compare to Figure 3, which uses full-sample ranks.

A.7 Cognitive Ability Sub-Scores

The overall cognitive ability score combines four distinct subtests: inductive reasoning (logical thinking), verbal knowledge, spatial ability, and technical understanding. Table A9 examines the gradient for each subcomponent.

Table A9: Ability Gradients by Cognitive Sub-Score.

	(1) LI	(2) CI
Logical thinking	0.131 (0.001)	0.336 (0.004)
Verbal knowledge	0.045 (0.001)	0.191 (0.004)
Spatial ability	0.017 (0.001)	0.067 (0.003)
Technical knowledge	0.054 (0.001)	0.187 (0.003)
Obs	1,158,216	953,343
R^2	0.063	0.068

Log specifications on the positive-income sample. CI uses the financial capital income measure (dividends + interest + net capital gains). All sub-scores are standardized. All components have larger log coefficients for capital income than for labor income, with logical thinking showing the largest differential. The correlation between the overall stanine score and the sum of subscores is 0.98.

Logical thinking shows the largest differential, followed by verbal and technical knowledge of similar magnitude; spatial ability shows the smallest.

A.8 Other Abilities

The multivariate specification in Panel B of Table A10 is particularly informative. For labor income, both cognitive and non-cognitive ability are important predictors (0.138 and 0.166) when all three measures are included, broadly consistent with Lindqvist and Vestman (2011). For capital income, cognitive ability (0.521) substantially exceeds non-cognitive ability (0.325). Both ability types predict capital income, but the cognitive gradient is roughly 60 percent larger in the multivariate specification, suggesting that the skills associated with financial decision-making differ from those rewarded in workplace settings. Panels C–D report rank specifications, which confirm the same ranking: cognitive ability is the strongest predictor of capital income in both univariate and multivariate rank regressions.

Table A10: Gradients by Ability Type.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive		Non-cognitive		Height	
	Labor income	Capital income	Labor income	Capital income	Labor income	Capital income
Cognitive	0.207 (0.001)	0.653 (0.003)				
Non-cognitive			0.224 (0.001)	0.527 (0.003)		
Height					0.071 (0.001)	0.209 (0.003)
Obs	1,222,803	1,007,254	1,194,499	986,021	1,210,175	997,556
R^2	0.060	0.067	0.068	0.046	0.015	0.016

Panel B	Labor income	Capital income
Cognitive	0.138 (0.001)	0.521 (0.003)
Non-cognitive	0.166 (0.001)	0.325 (0.003)
Height	0.028 (0.001)	0.092 (0.003)
Obs	1,184,789	978,479
R^2	0.088	0.080

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive		Non-cognitive		Height	
	Labor income	Capital income	Labor income	Capital income	Labor income	Capital income
Cognitive	9.274 (0.024)	7.344 (0.025)				
Non-cognitive			9.062 (0.025)	6.001 (0.026)		
Height					3.081 (0.025)	2.365 (0.026)
Obs	1,254,054	1,254,244	1,224,633	1,224,820	1,240,553	1,240,743
R^2	0.126	0.072	0.120	0.050	0.035	0.016

Panel D	Labor income	Capital income
Cognitive	6.621 (0.026)	5.761 (0.028)
Non-cognitive	6.319 (0.027)	3.637 (0.028)
Height	1.223 (0.024)	0.968 (0.026)
Obs	1,214,299	1,214,486
R^2	0.167	0.084

Panels A–B: log specifications (univariate and multivariate). Panels C–D: rank specifications (percentile rank 0–100). Both use the financial capital income measure (dividends + interest + net capital gains).

A.9 GPA and Gender

Table 11 (in the main text) uses high school GPA and math grades as alternative ability measures available for both men and women. The capital gradient exceeds the labor gradient for both genders in both log and rank specifications.

A.10 Education and Occupation Controls

Table A11: Ability Gradients Controlling for Education and Occupation.

Panel A: Log Labor Income	(1)	(2)	(3)
Cognitive ability	0.178 (0.001)	0.124 (0.001)	0.073 (0.001)
Controls included	None	Edu	Edu + Occ
Observations	964,139	949,216	949,216
R^2	0.035	0.074	0.362
Panel B: Log Capital Income			
Cognitive ability	0.639 (0.003)	0.402 (0.003)	0.292 (0.003)
Controls included	None	Edu	Edu + Occ
Observations	964,136	949,216	949,216
R^2	0.066	0.096	0.136
Panel C: Rank Labor Income			
Cognitive ability	9.569 (0.024)	6.505 (0.028)	3.268 (0.024)
Controls included	None	Edu	Edu + Occ
Observations	1,243,235	1,215,508	1,215,508
R^2	0.128	0.188	0.459
Panel D: Rank Capital Income			
Cognitive ability	7.285 (0.025)	4.630 (0.025)	3.400 (0.025)
Controls included	None	Edu	Edu + Occ
Observations	1,243,234	1,215,507	1,215,507
R^2	0.071	0.098	0.133

Education controls: level and field. Occupation controls: 113 three-digit codes. CI uses the financial capital income measure (dividends + interest + net capital gains). Panels A–B use log specifications on the positive-income sample; Panels C–D use rank specifications on the unrestricted sample.

A.11 Family Background

Table A12: Ability Gradients Controlling for Family Background and Bequests.

Panel A: Log specifications						
Par. Income	(1)	(2)	(3)	(4)	(5)	(6)
	Labor income			Capital income		
Cognitive ability	0.207 (0.001)	0.195 (0.001)	0.198 (0.002)	0.653 (0.003)	0.651 (0.003)	0.505 (0.005)
Par. LI		0.073 (0.001)			0.036 (0.003)	
Par. CI			−0.001 (0.001)			0.293 (0.003)
Obs	1,222,803	1,201,227	260,302	1,007,254	989,810	230,399
R^2	0.060	0.064	0.054	0.067	0.068	0.097
Family FE	Labor income			Capital income		
Cognitive ability	0.207 (0.001)		0.162 (0.002)	0.653 (0.003)		0.359 (0.007)
Family FE	No		Yes	No		Yes
Obs	1,222,803		521,974	1,007,254		427,653
R^2	0.060		0.029	0.067		0.014
Bequests	Labor income			Capital income		
Cognitive ability	0.217 (0.002)		0.214 (0.002)	0.654 (0.006)		0.620 (0.006)
Bequest > 0			0.065 (0.004)			0.728 (0.012)
Obs	227,642		227,642	193,308		193,308
R^2	0.060		0.061	0.067		0.085
Panel B: Rank specifications						
Par. Income	Rank labor income			Rank capital income		
Cognitive ability	9.274 (0.024)	8.434 (0.025)	9.244 (0.052)	7.344 (0.025)	7.020 (0.026)	5.837 (0.054)
Obs	1,254,054	1,231,527	266,367	1,254,244	1,231,708	266,412
R^2	0.126	0.141	0.118	0.072	0.075	0.102
Family FE	Rank labor income			Rank capital income		
Cognitive ability	9.274 (0.024)		7.301 (0.063)	7.344 (0.025)		3.543 (0.063)
Family FE	No		Yes	No		Yes
Obs	1,254,054		534,026	1,254,244		534,105
R^2	0.126		0.068	0.072		0.014
Bequests	Rank labor income			Rank capital income		
Cognitive ability	9.698 (0.055)		9.567 (0.055)	7.546 (0.057)		7.048 (0.057)
Bequest > 0			2.331 (0.115)			8.887 (0.119)
Obs	233,677		233,677	233,703		233,703
R^2	0.127		0.129	0.074		0.096

Par. LI/CI = parental labor/capital income when child is 16–20. Bequest data cover inheritances received by sample members from individuals who died between July 2001 and December 2005. CI uses the financial capital income measure (dividends + interest + net capital gains). Panel A uses log specifications on the positive-income sample; Panel B uses rank specifications (percentile rank 0–100) on the unrestricted sample.

A.12 Excluding Self-Employed

Table A13: Ability Gradients Excluding Self-Employed.

	(1)	(2)	(3)	(4)
Panel A: Log specifications				
	Labor income			
Cognitive ability	0.178 (0.001)	0.180 (0.001)	0.178 (0.001)	0.180 (0.001)
Owners of closely held corporations	Included	Excluded	Included	Excluded
Unincorporated business owners	Included	Included	Excluded	Excluded
Obs	982,640	918,483	920,713	856,556
R^2	0.057	0.056	0.064	0.063
	Capital income			
Cognitive ability	0.644 (0.003)	0.646 (0.003)	0.657 (0.003)	0.660 (0.003)
Owners of closely held corporations	Included	Excluded	Included	Excluded
Unincorporated business owners	Included	Included	Excluded	Excluded
Obs	964,136	899,982	916,995	852,841
R^2	0.066	0.066	0.068	0.068
Panel B: Rank specifications				
	Labor income			
Cognitive ability	9.569 (0.024)	9.613 (0.024)	9.772 (0.024)	9.848 (0.025)
Owners of closely held corporations	Included	Excluded	Included	Excluded
Unincorporated business owners	Included	Included	Excluded	Excluded
Obs	1,243,235	1,172,499	1,169,322	1,098,586
R^2	0.128	0.128	0.138	0.139
	Capital income			
Cognitive ability	7.285 (0.025)	7.240 (0.025)	7.515 (0.025)	7.479 (0.025)
Owners of closely held corporations	Included	Excluded	Included	Excluded
Unincorporated business owners	Included	Included	Excluded	Excluded
Obs	1,243,234	1,172,498	1,169,321	1,098,585
R^2	0.071	0.071	0.074	0.075

Column 1 includes all; columns 2–4 exclude various self-employed categories. CI uses the financial capital income measure (dividends + interest + net capital gains). Panel A uses log specifications on the positive-income sample; Panel B uses rank specifications on the unrestricted sample.

A.13 Excluding Outliers

Table A14: Ability Gradients Excluding Outliers.

	(1)	(2)	(3)	(4)
	Logs		Levels, excl. tails	
	LI	CI	LI	CI
Cognitive ability	0.209	0.649	4.465	0.400
	(0.001)	(0.003)	(0.012)	(0.002)
Obs	1,214,246	996,679	1,200,182	1,218,561
R^2	0.060	0.066	0.125	0.033
Mean			23.39	1.00
Beta/Mean			0.191	0.40

Columns 1–2: log specifications (positive-income sample). Columns 3–4: level specifications excluding extreme tails. CI uses the financial capital income measure (dividends + interest + net capital gains).

A.14 Controlling for Age at Test

The exact age at which the enlistment test is taken varies across individuals and may not be random, as enrollment offices had information on date of birth and parish when assigning test days (see Carlsson et al., 2015, for analysis of age-at-test effects). We therefore re-estimate our effects controlling flexibly for age at test in months.

Table A15: Ability Gradients Controlling for Age at Test.

	(1)	(2)	(3)	(4)
			Both incomes > 0	
	LI	CI	LI	CI
Panel A: Log specifications				
Cognitive ability	0.207 (0.001)	0.645 (0.003)	0.177 (0.001)	0.635 (0.003)
Obs	1,213,737	996,337	982,584	982,584
R^2	0.060	0.066	0.058	0.066
Panel B: Rank specifications				
Cognitive ability	9.525 (0.024)	7.241 (0.025)	8.829 (0.027)	6.789 (0.028)
Obs	1,242,669	1,242,668	982,319	982,319
R^2	0.128	0.071	0.121	0.067

Controls include flexible age-at-test dummies (in months). CI uses the financial capital income measure (dividends + interest + net capital gains). Panel A uses log specifications; Panel B uses rank specifications (percentile rank 0–100).

A.15 Taxation

Table A16: Ability Gradients Before and After Tax.

	(1)	(2)	(3)	(4)
	Labor income		Capital income	
	Before tax	After tax	Before tax	After tax
Panel A: Log specifications				
Cognitive ability	0.161 (0.001)	0.081 (0.001)	0.383 (0.004)	0.382 (0.004)
Obs	280,529	280,529	280,529	280,529
R^2	0.077	0.079	0.084	0.076
Panel B: Rank specifications				
Cognitive ability	9.147 (0.024)	7.076 (0.024)	0.716 (0.026)	0.259 (0.026)
Obs	1,225,093	1,225,093	1,225,093	1,225,093
R^2	0.135	0.134	0.015	0.016

Panel A: log specifications. Panel B: rank specifications (percentile rank 0–100). Capital income is taxable capital income from the tax register (KKAP), the statutory base to which the proportional capital tax applies. Labor income uses the broad taxable definition including transfers (CTXFVI). In the log specification, the capital income coefficient is essentially unchanged after taxation, while the labor income coefficient declines substantially. In the rank specification, both coefficients decline after taxation.

Table A17: Ability and Paid Taxes.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total taxes		Labor taxes		Capital taxes	
Panel A: Log specifications						
Cognitive ability	0.189 (0.001)	0.075 (0.001)	0.177 (0.001)	0.039 (0.001)	0.348 (0.003)	0.291 (0.003)
Lab. income		0.555 (0.002)		0.662 (0.003)		0.305 (0.004)
Obs	1,221,745	1,221,745	1,206,926	1,206,926	679,422	679,422
R^2	0.118	0.612	0.067	0.594	0.072	0.084
Panel B: Rank specifications						
Cognitive ability	9.478 (0.023)	1.443 (0.013)	9.549 (0.024)	0.606 (0.009)	8.047 (0.032)	6.904 (0.034)
Rank lab. income		0.866 (0.000)		0.951 (0.000)		0.123 (0.001)
Obs	1,254,054	1,254,054	1,232,783	1,232,783	1,254,053	1,254,053
R^2	0.148	0.805	0.125	0.900	0.050	0.058

Panel A: taxes in logarithmic form, averaged over 1998–2007. Panel B: rank specifications (percentile rank 0–100).

A.16 Lifecycle Patterns

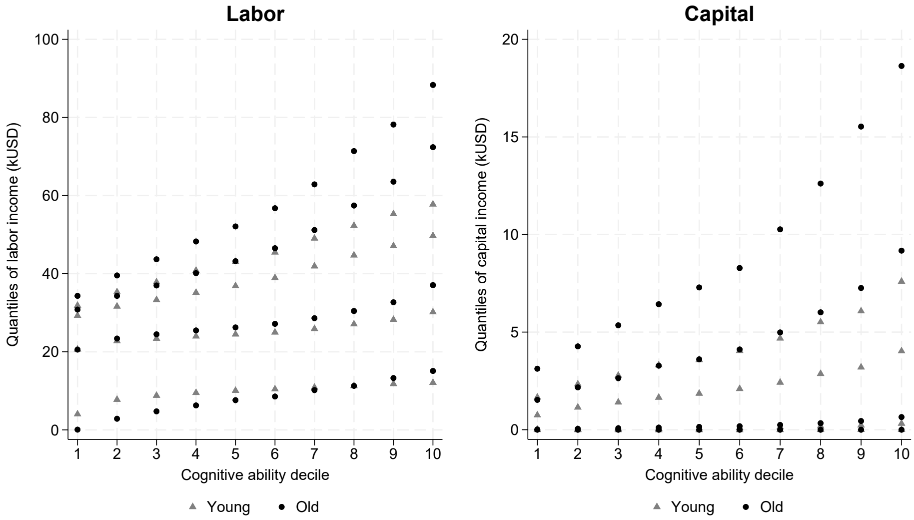
Our sample spans birth cohorts 1951–1975 observed during 1998–2007, creating variation in age at observation:

- *Young cohorts*: born 1968–1975 (average age 26–37)
- *Middle cohorts*: born 1959–1967 (average age 34–48)
- *Old cohorts*: born 1951–1958 (average age 43–56)

Prior research suggests ability gradients in labor markets increase with experience as employers learn about worker productivity (Farber and Gibbons, 1996; Altonji and Pierret, 2001); Falch and Sandgren Massih (2012) document similar patterns in a Swedish context using data similar to ours. For capital markets, the prediction is less clear: compounding returns and longer investment horizons favor older individuals, but the quality of financial decisions in credit markets peaks around ages 50–55 (Agarwal et al., 2009), suggesting that cognitive decline may offset experience gains at older ages.

Figure A2 shows income dispersion within each ability decile, separately for young and old cohorts. Income dispersion increases with cognitive ability for both income types, but the pattern is more pronounced for capital income. The ability gradient is present for both cohorts, but older cohorts show greater income dispersion at all ability levels, consistent with lifecycle accumulation.

Figure A2: Income Quantiles by Cognitive Ability Decile.



Panel A: Labor income. Panel B: Capital income. Triangles: young cohorts (born 1966–1975, average age 28–37). Circles: old cohorts (born 1951–1960, average age 43–56). The figure uses a coarser two-group split than the regression tables for visual clarity. Within each ability decile, we plot the 10th, 50th, 90th, and 95th percentiles of income.

Table A18: Ability Gradients by Age Group.

	Young (26–37)	Middle (34–48)	Old (43–56)
Panel A: Log Labor Income			
Cognitive ability	0.152 (0.001)	0.233 (0.002)	0.239 (0.002)
Observations	406,808	424,328	382,789
Panel B: Log Capital Income			
Cognitive ability	0.626 (0.005)	0.688 (0.005)	0.631 (0.005)
Observations	325,855	342,936	327,888
Panel C: Rank Labor Income			
Cognitive ability	7.388 (0.040)	10.656 (0.040)	10.601 (0.043)
Observations	412,266	434,159	396,810
Panel D: Rank Capital Income			
Cognitive ability	7.088 (0.042)	7.652 (0.043)	7.101 (0.045)
Observations	412,266	434,158	396,810
Panel E: Saving (conditional on income)			
Cognitive ability	0.249 (0.004)	0.197 (0.004)	0.146 (0.004)
Panel F: Portfolio Return (pp)			
Cognitive ability	0.511 (0.089)	0.299 (0.080)	0.534 (0.070)
Capital/Labor Ratio (logs)	4.12	2.95	2.64
Capital/Labor Ratio (ranks)	0.96	0.72	0.67

Panels A–B: log specifications. Panels C–D: rank specifications (percentile rank 0–100). Panels E–F: conditional on log labor income. Young: born 1968–1975; Middle: born 1959–1967; Old: born 1951–1958.

An important caveat is that cross-cohort comparisons conflate age and cohort effects. Older cohorts may differ from younger ones not only because they are observed at older ages, but also because they experienced different economic environments. The within-sample variation cannot fully separate age from cohort effects without panel data following individuals over time.

To formally test whether ability gradients vary with age, we interact standardized cognitive ability with average age:

$$Y_{ia} = \beta_1 \theta_i + \beta_2(\theta_i \times \overline{age}_i) + \gamma \overline{age}_i + \alpha_a + \varepsilon_{ia}. \tag{A.7}$$

Table A19: Age Interactions with Cognitive Ability.

Panel A: Log specifications	Log Labor	Log Capital	Log Saving	Portfolio Return
Cognitive ability (β_1)	0.208	0.649	0.198	0.447
	(0.001)	(0.003)	(0.002)	(0.046)
Cog. ability × Age (β_2)	0.0053	0.0002	−0.0076	−0.0030
	(0.0001)	(0.0004)	(0.0003)	(0.0058)
Observations	1,213,925	996,679	747,728	464,223
Panel B: Rank specifications	Rank Labor	Rank Capital		
Cognitive ability (β_1)	9.539	7.285		
	(0.024)	(0.025)		
Cog. ability × Age (β_2)	0.1953	−0.0002		
	(0.0033)	(0.0034)		
Observations	1,243,235	1,243,234		

Age centered at sample mean. Positive β_2 indicates ability gradient increases with age. Panel A: log specifications; columns 3–4 control for log labor income. Panel B: rank specifications (percentile rank 0–100) on the unrestricted sample.

A positive β_2 for labor income would be consistent with employer learning models. A larger positive β_2 for capital income would suggest the capital-income gradient grows over the lifecycle. A positive β_2 for saving would indicate that ability's effect on wealth accumulation strengthens with age.

Within-Cohort Comparison. Table A18 compares different cohorts at different ages, conflating age and cohort effects. To address this, we split the observation period into two subperiods (1998–2002 and 2003–2007) and estimate ability gradients separately for each cohort group in each period. This allows us to observe the *same* cohorts five years apart, partially disentangling age from cohort effects.

Table A20: Within-Cohort Lifecycle: Ability Gradients Across Sub-Periods.

	Period 1 (1998–2002)			Period 2 (2003–2007)		
	Young	Middle	Old	Young	Middle	Old
Panel A: Log Labor Income						
Cognitive ability	0.113	0.219	0.221	0.157	0.217	0.220
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	404,120	421,272	380,457	399,737	416,019	372,140
Panel B: Log Capital Income						
Cognitive ability	0.584	0.662	0.581	0.588	0.622	0.594
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	291,490	313,141	304,849	310,006	328,338	312,658
Capital/Labor Ratio (logs)	5.17	3.02	2.63	3.75	2.87	2.70
Panel C: Rank Labor Income						
Cognitive ability	5.906	10.209	10.358	7.663	9.930	9.947
	(0.038)	(0.039)	(0.042)	(0.042)	(0.042)	(0.045)
Observations	414,247	435,883	398,870	411,198	433,262	395,186
Panel D: Rank Capital Income						
Cognitive ability	6.841	7.424	6.561	6.861	7.373	6.896
	(0.043)	(0.044)	(0.045)	(0.045)	(0.045)	(0.047)
Observations	414,236	435,875	398,867	411,190	433,246	395,183
Capital/Labor Ratio (ranks)	1.16	0.73	0.63	0.90	0.74	0.69

Panels A–B: log specifications. Panels C–D: rank specifications (percentile rank 0–100). Young: born 1968–1975 (age ∼28 in period 1, ∼33 in period 2). Middle: born 1959–1967 (age ∼36/∼41). Old: born 1951–1958 (age ∼45/∼50). All specifications include cohort fixed effects; results without are nearly identical.

The results reveal clear employer learning in labor markets: the young cohort's labor coefficient rises from 0.113 to 0.157 between periods (a 39% increase), consistent with employers gradually learning about worker ability. For middle-aged and older cohorts, labor coefficients are stable. Capital income coefficients, by contrast, remain stable across periods for all cohorts (∼0.58–0.66), suggesting that the ability–capital income relationship does not grow with age in the same way. The capital-to-labor ratio consequently declines for the young (from 5.17 to 3.75) as their labor returns catch up, while remaining stable around 2.6–3.0 for older cohorts. Results are virtually identical with and without cohort fixed effects.

B Supplementary Material for Decomposition and Financial Behavior

B.1 Cohort Fixed Effects in Saving and Returns

To assess the importance of birth cohort fixed effects in our mechanism analysis, Table A21 compares estimates with and without cohort fixed effects for saving and portfolio returns.

Table A21: Saving and Returns: Sensitivity to Cohort Fixed Effects.

	(1)	(2)	(3)	(4)
	Log Saving		Portfolio Return (pp)	
	No Cohort FE	With Cohort FE	No Cohort FE	With Cohort FE
Cognitive ability	0.343	0.333	0.452	0.451
	(0.002)	(0.002)	(0.042)	(0.042)
Observations	783,413	783,413	485,613	485,613
R^2	0.039	0.057	0.000	0.000

Unconditional estimates of $Y_{ia} = \alpha_a + \beta Cog_i + \varepsilon_{ia}$ with and without birth cohort fixed effects, not controlling for labor income. Adding cohort fixed effects has minimal impact on both the saving and portfolio return coefficients, indicating that ability's effects are not confounded by cohort differences.

B.2 Descriptive Statistics for Decomposition Sample

The decomposition analysis in Sections 5–6 uses a subsample of individuals with financial asset holdings. Table A22 provides descriptive statistics for this subsample, including participation rates and the distribution of financial behaviors by cognitive ability group.

Table A22: Descriptive Statistics for the Decomposition and Financial Behavior Samples.

	1 (Low)	2	3	4	5 (High)
Panel A: Sample Sizes and Participation					
N in full sample	260,186	188,876	273,720	211,536	308,952
% with positive financial wealth	82.5	89.4	92.3	94.4	96.5
% with positive saving	80.9	80.5	79.5	78.5	77.0
% with non-zero portfolio returns	35.4	42.5	47.0	52.7	59.3
Panel B: Mean Financial Outcomes (conditional)					
Mean saving (1000 USD)	0.83	1.02	1.10	1.43	1.82
Mean portfolio return (%)	6.95	7.61	8.11	8.49	8.33
Mean financial wealth (1000 USD)	10.67	15.08	16.79	21.78	33.19
Panel C: Asset Ownership Rates (%)					
Direct stockholding	32.6	40.2	45.6	51.5	58.6
Equity mutual funds	50.0	55.8	59.5	62.8	66.7
Bond mutual funds	18.1	18.2	18.6	19.4	21.2

Cognitive ability groups defined within the full sample using stanine scores: group 1 = stanines 1–3, group 2 = stanine 4, group 3 = stanine 5, group 4 = stanine 6, group 5 = stanines 7–9. Panel A shows sample sizes and participation rates conditional on positive financial wealth. Panel B conditions on positive values. Panel C shows ownership rates for specific asset types among those with positive financial wealth.

B.3 Nonparametric Income Controls

Table A23 estimates the effect of cognitive ability on saving while controlling for labor or disposable income non-parametrically using dummies for deciles of income.

Table A23: Ability, Saving, and Portfolio Returns with Income Decile Dummies.

	(1)	(2)	(3)	(4)
	Panel A: Saving			
Cognitive ability	0.190 (0.002)	0.205 (0.022)	0.184 (0.020)	0.172 (0.002)
Labor income dummies	Yes	Yes	Yes	No
Disposable income dummies	No	No	No	Yes
Excl. saving ≤ 0	Yes	No	Yes	Yes
Excl. labor income < \$15,000	Yes	Yes	Yes	No
Excl. saving > 100% of disp. income	No	No	Yes	Yes
Obs	783,392	1,004,866	759,359	878,569
R^2	0.102	0.001	0.105	0.131
	(1)	(2)	(3)	(4)
	Panel B: Portfolio Return			
Cognitive ability $\times 100$	0.452 (0.046)	0.747 (0.021)	1.176 (0.023)	0.421 (0.043)
Labor income dummies	Yes	Yes	Yes	No
Disposable income dummies	No	No	No	Yes
Conditional on having returns	Yes	No	No	Yes
Excl. labor income < \$15,000	Yes	Yes	Yes	No
Obs	485,606	1,004,866	1,004,866	548,647
R^2	0.001	0.005	0.012	0.001

Panel A: dependent variable is saving. Specification uses income decile dummies $D(Z_L)_m$ instead of log income. Columns 1, 3, and 4 use $\log(S_{ia})$, excluding negative savings. Column 2 uses levels, normalizing coefficients by mean saving. Columns 3–4 exclude individuals saving more than 100% of disposable income. Column 4 uses disposable income deciles instead of labor income deciles. Panel B: dependent variable is portfolio return r_{ia} in percentage points. Specification uses income decile dummies. Column 1 includes only individuals with marketable financial assets. Column 2 assigns $r = -0.01$ (risk-free rate) to non-investors. Column 3 assigns $r = -0.08$ (average market return) to non-investors. Column 4 uses disposable income deciles.

B.4 Non-Cognitive Ability

Table A24: Non-Cognitive Ability, Saving, and Portfolio Returns.

	(1)	(2)	(3)	(4)
		Panel A: Saving		
Non-cognitive ability	0.095 (0.002)	0.003 (0.020)	0.089 (0.002)	0.117 (0.002)
Log of labor income	1.209 (0.005)	1.342 (0.257)	1.233 (0.005)	-
Log of disposable income	-	-	-	1.265 (0.006)
Obs	767,241	984,105	743,620	858,713
R^2	0.098	0.001	0.101	0.121
		Panel B: Portfolio Return		
Non-cognitive ability ×100	0.344 (0.047)	0.510 (0.022)	0.788 (0.023)	0.290 (0.047)
Log of labor income	0.084 (0.113)	2.573 (0.067)	4.539 (0.070)	-
Log of disposable income	-	-	-	0.604 (0.123)
Obs	477,897	984,105	984,105	477,892
R^2	0.001	0.004	0.009	0.001

Same specifications as Table 6 but using non-cognitive ability.

B.5 Non-Cognitive Ability: Excess Return and Risk

Table A25: Non-Cognitive Ability and Excess Return and Risk.

	(1) Excess Return (α)	(2) Risk (β)
Non-cognitive ability	0.600 (0.094)	0.043 (0.004)
Log of labor income	0.068 (0.114)	0.005 (0.001)
Mean	5.00	1.08
Obs	506,796	506,796
R^2	0.001	0.012

Same specifications as Table 8 but using non-cognitive ability.

B.6 Saving Including Debt

Table A26: Ability and Saving Including Changes in Debt.

	(1)	(2)	(3)	(4)
	Saving			
Cognitive ability	0.107 (0.002)	0.119 (0.047)	0.100 (0.002)	0.120 (0.002)
Log of labor income	0.879 (0.006)	1.918 (0.490)	0.821 (0.005)	-
Log of disposable income	-	-	-	1.104 (0.005)
Excl. saving ≤ 0	Yes	No	Yes	Yes
Excl. labor income $<$ \$15,000	Yes	Yes	Yes	No
Excl. saving $>$ 100% of z_L	No	No	Yes	Yes
Obs	541,452	1,004,866	532,066	639,631
R^2	0.092	0.006	0.096	0.168

The estimates are from the regression $Y(S_{ia}) = \alpha_a + \beta Cog_i + \gamma z_L + \varepsilon_{ia}$. In columns 1, 3, and 4, $Y(S) = \log(S)$, excluding observations with negative saving. Column 2 estimates saving in levels, normalizing the coefficients by average saving. Columns 3 and 4 limit saving to 100% of disposable income. In column 4, we replace labor income with disposable income.

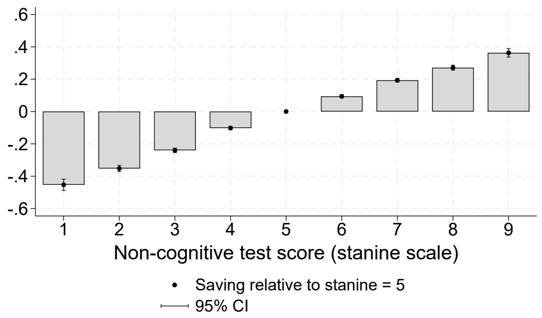
B.7 Financial Behavior

Table A27: Non-Cognitive Ability, Risky Asset Share, and Hand-to-Mouth Behavior.

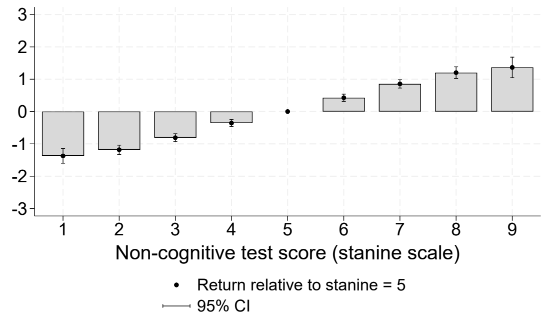
	(1)	(2)	(3)	(4)
	Risky asset share		Hand-to-mouth	
	FW $>$ 0	FW $>$ 0 & RA $>$ 0	Saving $<$ 3%	Saving $<$ 1.5%
Non-cognitive ability	2.185 (0.030)	0.058 (0.030)	-2.814 (0.035)	-1.673 (0.027)
Log of labor income	2.726 (0.041)	-1.271 (0.044)	-1.702 (0.042)	-1.515 (0.035)
Mean, in percent	33.90	46.23	15.68	8.51
Obs	1,094,388	807,783	1,185,829	1,185,829
R^2	0.015	0.002	0.010	0.001

Same as Table 9 but using non-cognitive ability.

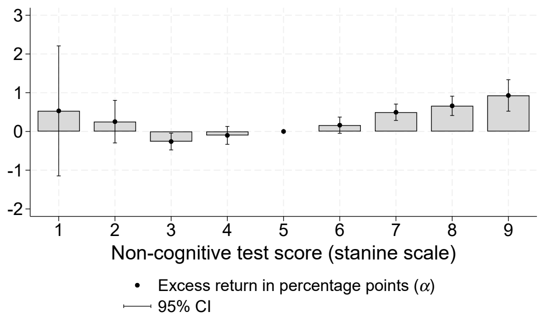
Figure A3: Non-Cognitive Ability Gradients in Financial Outcomes.



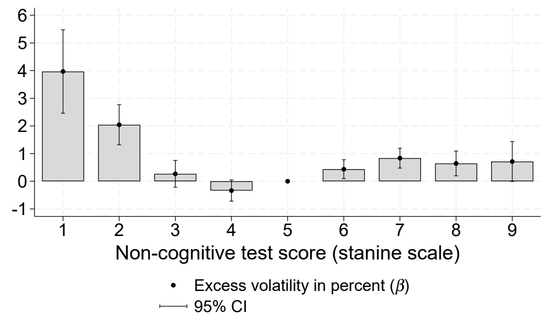
Panel A: Saving



Panel B: Asset return



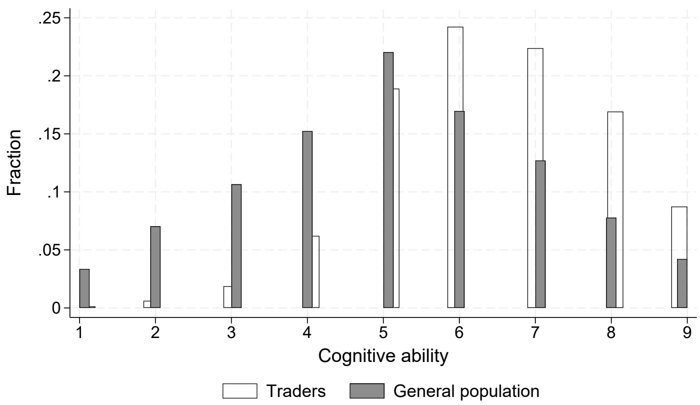
Panel C: Excess return



Panel D: Portfolio risk

Non-cognitive ability on stanine scale (1–9), with $NonCog = 5$ as reference category.

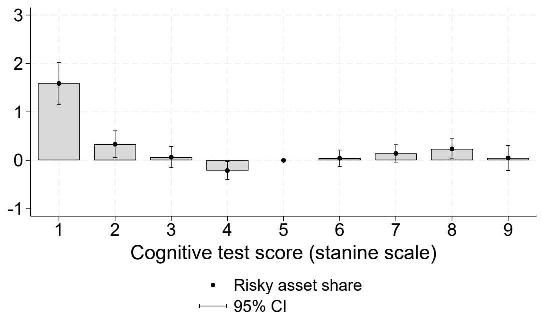
Figure A4: Distribution of Cognitive Ability for Financial Professionals.



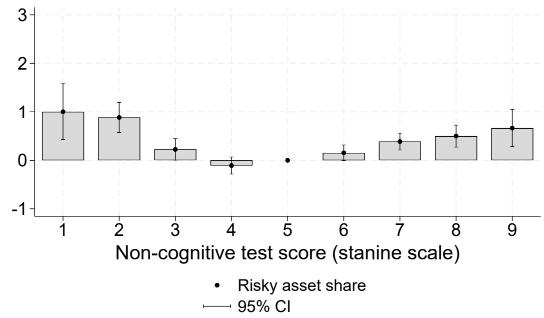
Distribution of raw cognitive test scores for the whole sample and for individuals employed as stock traders, fund administrators, and financial advisers. Financial professionals have markedly higher cognitive ability than the general population, with the distribution shifted significantly rightward.

Financial professionals (stock traders, fund administrators, and financial advisers) are concentrated in the upper tail of the cognitive ability distribution. This positive sorting into financially oriented occupations may partly explain the ability gradient in capital markets, alongside possible effects on investment skill.

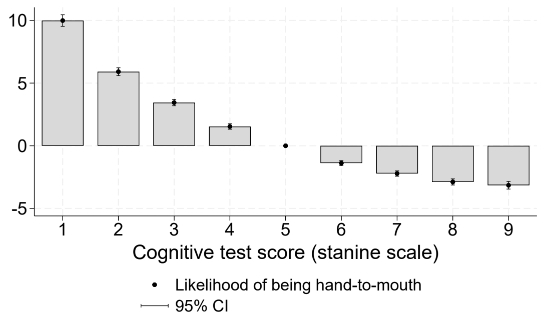
Figure A5: Ability Gradients in Risky Asset Shares and Hand-to-Mouth Behavior.



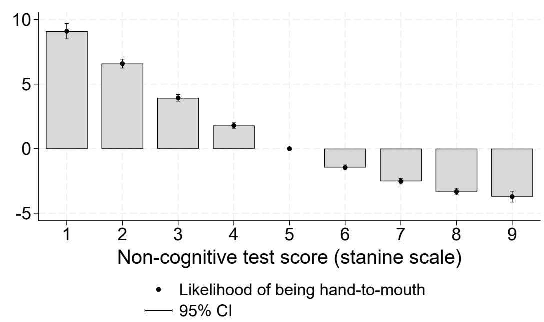
Panel A: Cognitive ability: Risky share (conditional)



Panel B: Non-cognitive ability: Risky share (conditional)



Panel C: Cognitive ability: Hand-to-mouth



Panel D: Non-cognitive ability: Hand-to-mouth

Panels A–B show risky asset share for individuals with positive risky assets. Panels C–D show hand-to-mouth probability. Reference category is stanine 5 in all panels.

Cognitive ability strongly predicts holding risky assets (extensive margin), but the risky asset share conditional on participation is essentially flat (Panels A–B). The effect operates through the participation decision, not the conditional allocation.

For hand-to-mouth behavior (Panels C–D), both ability types show strong gradients, steepest at the bottom: individuals at stanine 1 are more than 4 percentage points more likely to be hand-to-mouth than those at stanine 5.

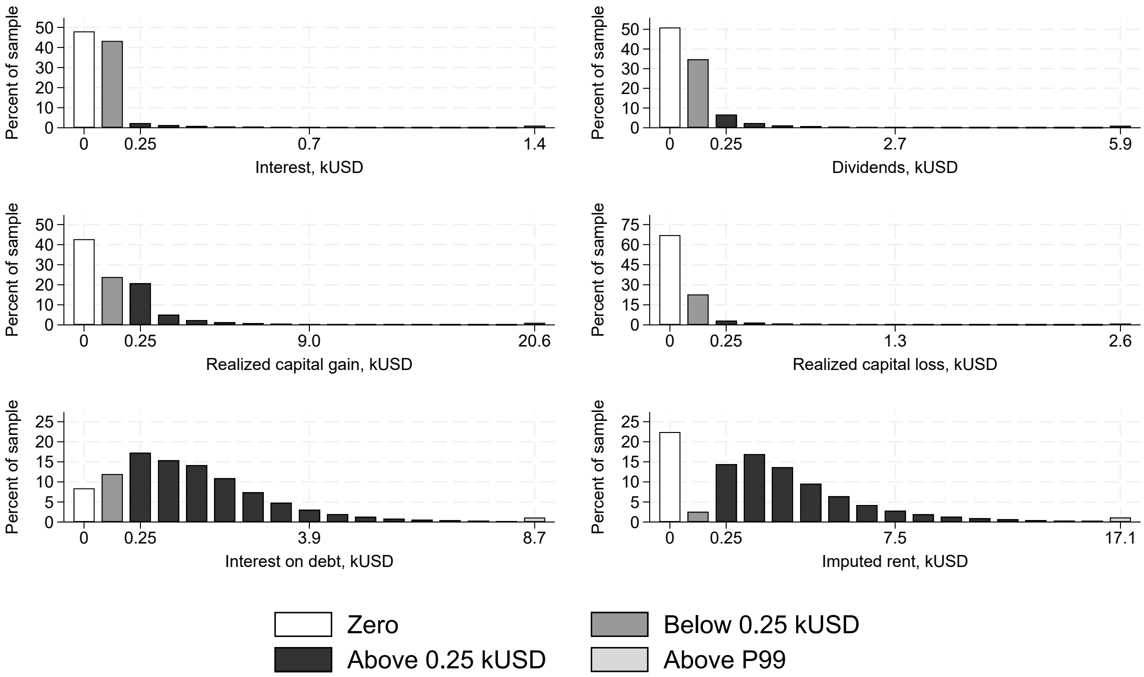
C Data Description

Table A28: 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	1,243,270
(3). Men in (2) with labor income > 0 (in 1998–2007)	1,213,925
(4). Men in (3) with non-missing information about level and field of education	1,192,143
(5). Men in (4) with non-missing information about occupation	1,080,240
(6). Men in (2) with financial capital income > 0 (in 1998–2007)	982,640
(7). Men in (2) with broad capital income > 0 (in 1998–2007)	866,767
(8). Men in (6) with non-missing information about level and field of education	966,337
(9). Men in (8) with non-missing information about occupation	887,137
(10). Men in (2) with taxable capital income > 0 (in 1998–2007)	290,678

Financial capital income = dividends + interest + net capital gains (baseline measure). Broad capital income additionally includes imputed rents minus debt interest. Capital income is taxable if the net of financial capital income minus debt interest payments is positive. For participation in different incomes and wealth components, see number of observations in regression tables.

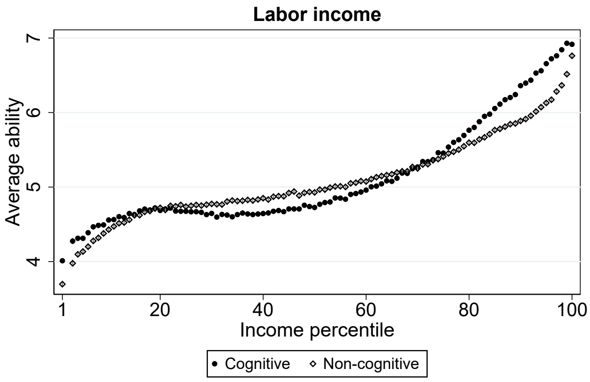
Figure A6: The Distribution of Capital Income Components.



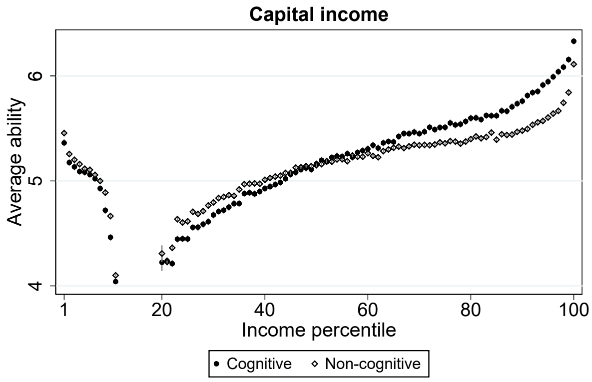
Values in thousands of USD, averaged over 1998–2007. Each panel shows the distribution of a single component. Bars are grouped by size: zero, below 0.25 kUSD, above 0.25 kUSD, and above the 99th percentile. Interest income and dividend income are the main positive financial income sources. Realized capital gains are highly skewed with mass at zero. Realized capital losses are less common. Debt interest payments represent the largest negative component for most households. Imputed rents provide housing returns for homeowners.

C.1 Average Ability by Income Percentile

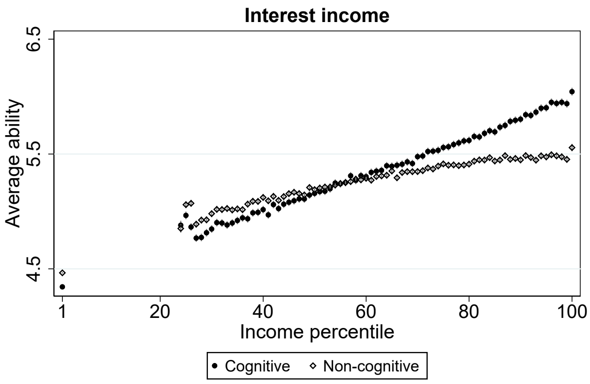
Figure A7: Average Cognitive and Non-cognitive Ability by Income Percentile.



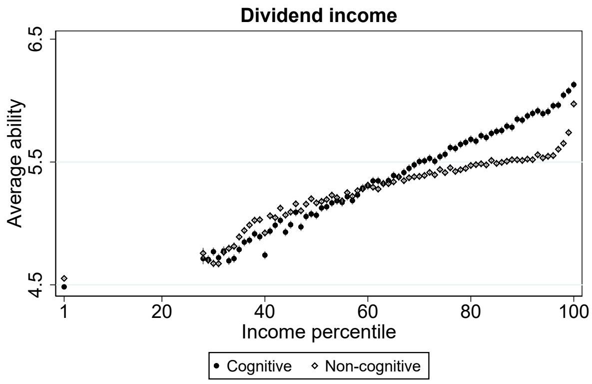
(a) Labor income



(b) Capital income



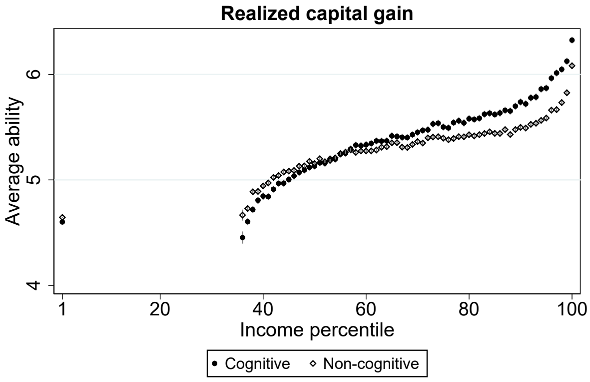
(c) Interest income



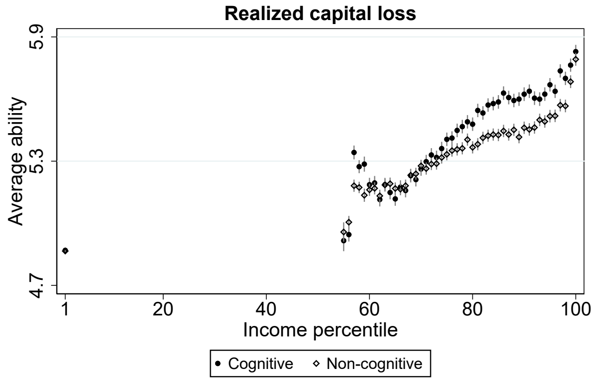
(d) Dividend income

Income percentiles are based on labor and capital income in levels. Filled dots: cognitive ability; open diamonds: non-cognitive ability.

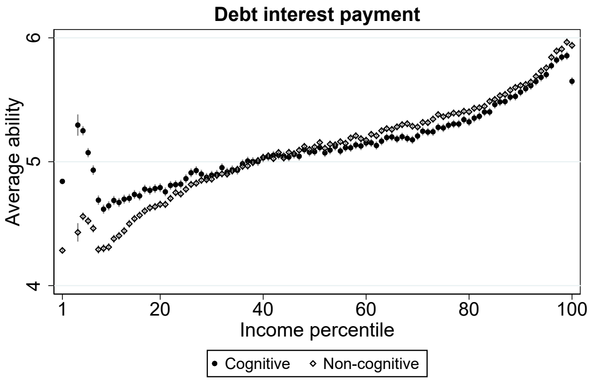
Figure A7: (Continued) Average Cognitive and Non-cognitive Ability by Income Percentile.



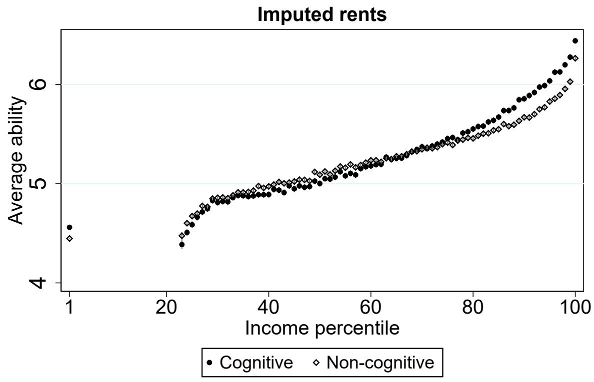
(e) Realized capital gain



(f) Realized capital loss



(g) Debt interest payment



(h) Imputed rents

Income percentiles are based on component-specific income in levels. Filled dots: cognitive ability; open diamonds: non-cognitive ability.

C.2 Saving and Returns in Micro and Macro Data

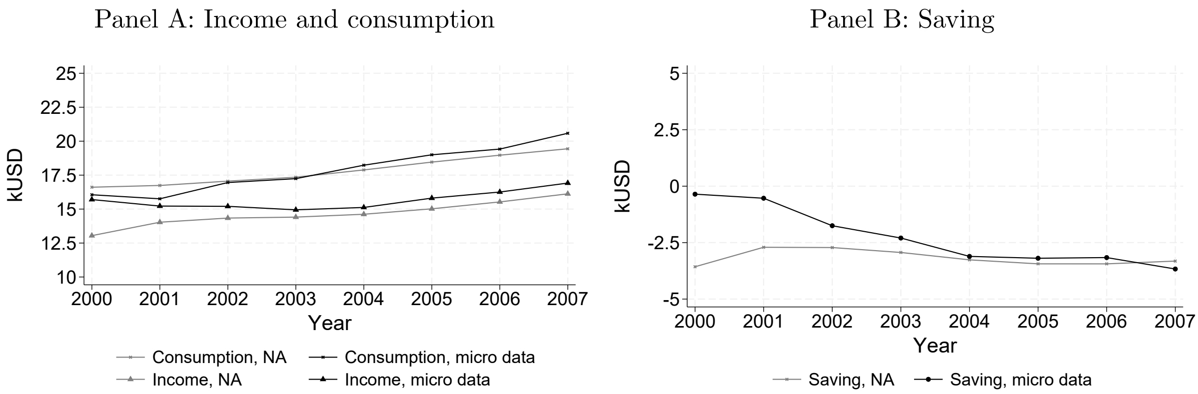
We compare our microdata measures of saving and returns against aggregate measures. We begin by comparing saving in the national accounts with our microdata measure. We calculate saving in the national accounts data as disposable income minus consumption.[38] Panel A of Figure A8 shows a high correspondence between disposable income and consumption in national accounts data and micro data for the period 2000–2007 for which both data sources are available. This translates into similar measures of saving as in Panel B. However, there are some differences at the beginning of the period, largely due to the fact that micro data on wealth were less comprehensive in the early 2000s.

[38]The national accounts measure of disposable income differs from our microdata measure of disposable income in important ways. For example, the national accounts measure includes imputed rents, which we subtract by multiplying real wealth by an average rate of return; see Gareis et al. (2023) for more information. For more on the comparison between national accounts consumption and our micro data, see Kolsrud et al. (2020).

We then compare the returns in our data with the aggregate returns. For the years 1999–2007, the average annual return on the Stockholm Stock Exchange was 21%. In our data the average return, defined by equation (3.2), is 40%. However, this number is heavily influenced by a small number of extreme values with average returns above 1,000%. Winsorizing returns at the top and bottom 0.1 percentiles yields an average annual return of 24%, while excluding extreme outliers, defined as observations above or below three standard deviations, yields an average annual return of 16%. Panel A of Figure A9 shows the distribution of returns truncated at the 99th percentile.

In addition, in Panel B of Figure A9 we plot weekly market returns for the Stockholm Stock Exchange 1999–2007. In the figure we also plot the average weekly return 1983–2019 and the average weekly return 1999–2007 along with a 95% confidence interval estimated for the period 1983–2019. During our study period, the average weekly return was 0.4 percentage points higher than the historical average. In addition, the stock market was less volatile, as indicated by only three observations outside the 95% confidence band. For a normally distributed variable, one would expect about 15 such occasions. This partially explains the small variation in the β risk measure across cognitive ability groups that we observe in our estimates.

Figure A8: Income, Consumption and Saving in National Accounts and Micro Data.

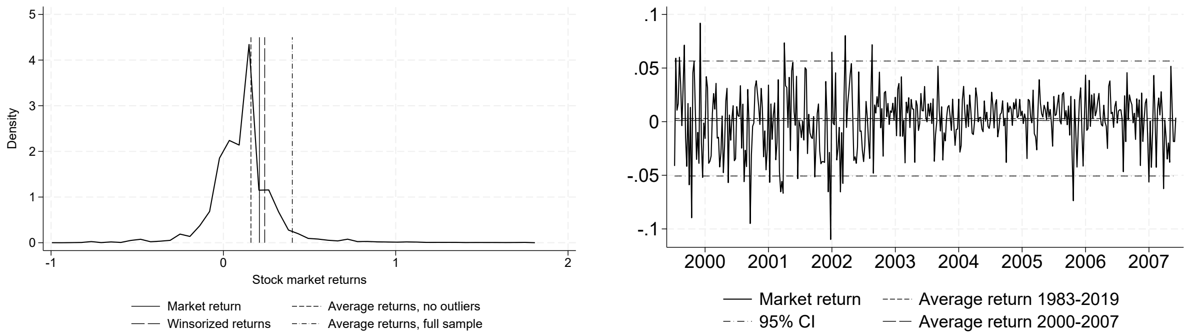


Panel A shows disposable income and consumption from our micro data and national accounts. Panel B shows saving, defined as the difference between disposable income and consumption. All values are in 2003 SEK and then converted to thousands of US dollars.

Figure A9: Returns in Micro and Aggregate Data.

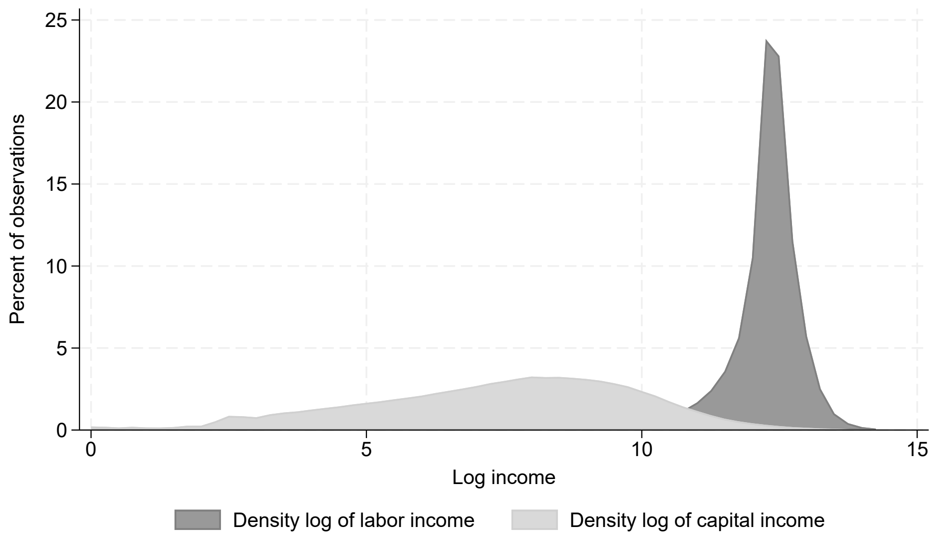
Panel A: The distribution of returns

Panel B: Variation in weekly market returns



Panel A shows the distribution of individual portfolio returns as measured by equation (3.2). The solid line is the density; vertical lines mark average returns under different sample restrictions: short-dashed after excluding observations beyond three standard deviations, long-dashed after winsorizing at the top 0.1 percentile, and dot-dashed for the full sample. Panel B shows weekly market returns on the Stockholm Stock Exchange in 2000–2007. The short-dashed line shows the average weekly return for 1983–2019 (data from the Swedish House of Finance), the long-dashed line shows the average for our study period, and the dot-dashed lines show a 95% confidence interval.

Figure A10: Distribution of Log Labor Income and Log Capital Income.



Kernel density estimates of log labor income and log capital income, restricted to positive values and truncated at the 99.9th percentile. The distributions differ markedly: log labor income is approximately symmetric around its mean, while log capital income has a much wider spread and substantial density near zero. This distributional difference underlies the metric sensitivity documented in Section 4.

C.3 Variable Definitions

Table A29: Variable Definitions and Sources.

Variable	Definition
Cognitive ability	Composite score from four subtests (inductive reasoning, vocabulary, spatial, technical) administered during military enlistment, standardized to mean 0 and SD 1.
Non-cognitive ability	Composite from psychologist assessments of social maturity, psychological energy, intensity, and emotional stability.
Labor income	Wages (TLONT) + active business income from sole proprietorships and partnerships (NAKTE + NAKTHB), excluding social insurance benefits.
Capital income (broad)	Interest + dividends + net capital gains + imputed rents − capital losses − debt interest.
Financial capital income	Dividends + interest + net realized capital gains (baseline measure, excluding housing components).
Saving	Active saving measured as $\sum_k p_{kt} \Delta Q_{ikt}$, i.e., changes in asset quantities valued at current prices.
Portfolio return	Asset-weighted price change: $(\sum_k p_{kt} Q_{ikt-1})/(\sum_k p_{kt-1} Q_{ikt-1})$.
Hand-to-mouth	Saving $<$ 3% of disposable income (primary definition).

All monetary variables in thousands of USD, averaged over the observation period.

Table A30: Variables from the Income and Tax Register.

Variables	Variable name in register
Labor income	TLONT + NAKTE + NAKTHB
Taxable labor income	CTXFVI
Labor income after tax	CTXFVI - SKLFVI - SSFVI
Interest income from bank deposit	KKURTA
Interest income from securities	KKUVP
Interest income	KKURTA + KKUVP
Dividend income	KKUUTD
Realized capital gain	KV
Realized capital loss	KF
Debt interest payment	KAKURTA
Capital income (broad)	KKUVP + KKURTA + KV + KKUUTD + imputed rents* - KF - KAKURTA
Financial capital income	KKUVP + KKURTA + KV + KKUUTD - KF
Taxable capital income	KKAP
Capital income after tax	KKAP - SKAP
Total tax	SSLUT

*Imputed rents are calculated by applying an assumed rate of return of 6.5% to the value of housing and co-ops.