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Economic Preferences Predict Higher-Education Choices*

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Abstract

We examine whether individual preferences predict higher education choices. According to standard human capital theory, differences in individuals' time and risk preferences lead to differences in educational investments. Testing this hypothesis is challenging, as it requires measuring individuals' preferences, doing so before they make educational investments, and subsequently observing their educational choices. We combine incentivized, experimentally elicited measures of time and risk preferences for a large, representative sample of 18–19-year-old Danes with administrative data on subsequent higher education choices, program-specific earnings trajectories, prior school performance, and family background. In line with theory, we find that more patient individuals choose longer education programs and programs with steeper early-career earnings profiles, while more risk-averse individuals select programs with lower earnings dispersion and reduced downside risk. These relationships remain strong after controlling for cognitive ability, prior academic performance, and family background. Our findings suggest that preferences have a substantial impact on real-world educational investments and have implications for educational sorting.

Keywords: Risk Preferences, Time Preferences, Educational Choices

JEL: I23, I24, I26, C91

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1 Introduction

Educational choices are among the most critical decisions young individuals face, influencing their lifetime earnings, career trajectories, and well-being. A long-standing hypothesis in economics, rooted in human capital theory (Becker, 1964), posits that economic preferences—such as patience and risk aversion—play a pivotal role in shaping these choices. For example, patient individuals should be more likely to prefer longer educational paths that yield returns later in life, while risk-averse individuals should shy away from fields where future earnings are uncertain, consistent with the risk-return framework articulated by Weiss (1972). Yet, despite the central role of preferences in these models, there is little direct empirical evidence on whether and how economic preferences predict educational choices.

To fill this gap, we conducted an incentivized preference-elicitation experiment—among the largest of its kind—covering a representative sample of more than 3,000 young Danes aged 18–19 on the verge of choosing higher education. Using state-of-the-art methods with monetary incentives, we elicited time and risk preference parameters of the individuals. Uniquely, these data are linked to administrative records on their subsequent educational choices, combined with earnings characteristics of these education choices and rich background information, including grade point average (GPA) at the end of compulsory schooling as well as parental education and income. The dataset allows us to test whether elicited preferences predict educational choices in patterns consistent with canonical human capital theory, while controlling for a rich set of ability and family background characteristics.

Importantly, preferences are elicited immediately before individuals make their post-secondary educational choices, allowing us to examine whether they predict subsequent choices. Moreover, our empirical evidence relies on individuals' relative positions in the distributions of time and risk preferences. Thus, our results do not depend on the exact measurement of the preference parameters, but only on the experiment's ability to identify who is more or less patient and risk averse than others.

To guide our empirical analysis, Table 1 presents an overview of theoretical hypotheses, as well as the specific educational outcome measures we use for the empirical analysis. Our results align with the theoretical predictions. We start by providing non-parametric graphical evidence showing clear univariate associations between preferences and education choices. More patient individuals in the experiment are significantly more likely to enroll in programs with longer durations as well as programs with higher expected labor earnings growth. Likewise, more risk-averse individuals

Table 1: Theoretical Predictions

Preference Dimension	Hypothesis and Implementation	Outcome	Predicted Effect
Patience	More patient individuals are willing to postpone earnings to achieve higher life-cycle earnings. (a) Higher patience ⇒ longer programs. (b) Higher patience ⇒ programs with higher earnings growth.	(a) Duration of applied-for program. (b) Higher labor earnings growth within program.	+
Risk aversion	More risk-averse individuals prefer educational programs offering more predictable earnings streams. (c) Higher risk aversion ⇒ programs with lower probability of low earnings. (d) Higher risk aversion ⇒ programs with lower earnings dispersion.	(c) Share of graduates with earnings $\leq$ P20. (d) Inter-quartile range of graduate labor earnings (P75–P25)/P50.	−

Notes: Hypotheses about the role of patience follow Becker's intertemporal investment model (Becker, 1964), while hypotheses about the role of risk aversion follow Weiss's expected-utility model of educational choice under earnings uncertainty (Weiss, 1972).

tend to enroll in educational programs with less cross-sectional dispersion in future earnings and programs with a lower likelihood of ending up in the bottom of the earnings distribution.

Cognitive ability and parental background are well-known, strong predictors of education choices and are also correlated with economic preferences (Dohmen et al., 2010, 2011). To isolate the predictive power of preferences, we include school GPA, parental education and income, as well as other controls in multivariate regressions. The preference parameters remain strong predictors of all four outcomes in Table 1. For example, we find that the predictive power of patience for education length is one-quarter of the predictive power of school GPA, while risk aversion is as predictive as GPA for choosing an education with low downside earnings risk.

Our results contribute to a large literature seeking to understand the drivers of higher education choices (Patnaik et al., 2021). This literature has focused primarily on the role of ability sorting and preferences for pecuniary and non-pecuniary attributes in shaping choices. Despite the centrality of time and risk preferences for decision-making under uncertainty in dynamic contexts, there is little direct evidence on whether experimentally elicited time and risk preferences predict individuals' actual higher-education choices. One reason for this gap is that it requires collecting these measures *prior* to the choice of higher education, collecting them at scale (which is uncommon for lab-in-the-field studies, where sample sizes are typically in the few hundred range), and linking these preference measures to administrative outcomes, which is often infeasible.

That said, there is a small literature that investigates whether time or risk preferences predict earlier educational outcomes. In particular, experimental studies demonstrate that impatience predicts behavioral problems and high-school completion, highlighting the role of time preferences for educational attainment at the extensive margin (Castillo et al., 2011, 2019). Relatedly, experimentally elicited patience also predicts secondary-school track choice (Angerer et al., 2023). Other work relies on survey-based measures of preferences. Golsteyn et al. (2014) show that a survey-based measure of time preferences in childhood predicts subsequent educational attainment and school-track enrollment. Earlier work also studies the relationship between survey-based measures of risk aversion and schooling attainment or transitions into higher education (Belzil and Leonardi, 2007). A related sociological literature similarly emphasizes the role of preferences in educational decisions, using survey-based preference measures and self-reported attainment of vocational and academic education (Breen et al., 2014). Somewhat related to our approach, Buser et al. (2014) collect incentivized measures of competitiveness from a sample of Dutch secondary-school students, and show that competitiveness is an important predictor of track choice.

Pervasive heterogeneity in time and risk preferences across individuals is well documented in the experimental literature (Mischel et al., 1989; Frederick et al., 2002; Bruhin et al., 2010; Charness et al., 2013). There is also a literature that examines how such heterogeneity predicts consequential real-life choices, such as health, savings, and crime (Sutter et al., 2013; Epper et al., 2020, 2022). Our results extend this literature to higher education choices. They have implications for modeling choice behavior. If individuals sort into higher education programs based not only on ability but also on time and risk preferences, assuming homogeneous time and risk preferences is an overly restrictive modeling choice and can lead to incorrect inference (Patnaik et al., 2022). More broadly, understanding how preferences predict educational choices helps explain why individuals sort into different educational paths and is relevant for understanding educational inequality.

2 The Danish Education System and Admission Process

The Danish education system is structured to provide individuals with flexible pathways for lifelong learning. After completing lower secondary education (typically at age 16), students choose between several upper secondary education tracks. These include academic tracks, such as the gymnasium (general upper secondary school), and vocational tracks focused on preparing students for specific trades. Completion of an academic track grants eligibility to apply for higher education, while vocational tracks often lead directly to employment, but may also provide pathways to further education.

Denmark offers a wide array of higher education options that differ substantially in length, orientation, and labor-market outcomes. These include university programs, which focus on academic and research-oriented education, and professional bachelor's degrees, which combine theoretical and practical learning geared towards specific careers. In addition, short-cycle academy programs and vocational academies offer specialized training for students seeking targeted skills in industries such as IT, business, or healthcare. This diversity ensures that students can pursue an education aligned with their abilities, preferences, and career aspirations.

The application process for further education in Denmark is centralized through the national Coordinated Admission System (KOT), through which prospective students submit ranked lists of preferred programs. Admission is primarily determined by upper secondary grade point average (GPA), with some programs requiring additional assessments or interviews. Higher education is tuition-free and all students are eligible for generous government stipends (SU) regardless of family background. This reduces the scope for financial constraints to shape educational choices relative to most other settings (Nielsen et al., 2010). The Danish context is therefore particularly well-suited for studying whether individual time and risk preferences can predict educational decisions, as observed differences in choices are less likely to reflect unequal access to funding.

3 Data

3.1 Experimental Elicitation of Preferences

Based on a random sample from population registries provided by Statistics Denmark, we conducted an incentivized online preference-elicitation experiment among 18-19-year-old individuals in Denmark in 2018. At this stage, individuals enrolled in upper secondary school are approaching—but have not yet made—their choice of higher education program. We invited 13,799 individuals to participate, all of whom received a personalized letter from the University of Copenhagen inviting them to participate on a customized internet platform. The invitations were distributed through an official electronic mailbox (Digital Post), which is the default way to receive mail from public authorities in Denmark. In our case, 39 percent of the invited individuals logged on to the platform.

For the elicitation of each preference parameter (time and risk preferences), the participants were presented with a series of choice situations, resembling methods previously used in the literature as described below. Before making decisions in these choice situations, participants watched an animated instruction video and completed a tutorial session. The choice situations were presented in random order. Each choice situation involved a monetary trade-off; for each participant, one choice situation was randomly selected to be paid out at the end of the session (with participants being informed about this at the beginning of the session). The average payment to the participants was DKK 250 (USD 40). After the random selection, participants typed their cell number and then the money was transferred through MobilePay, a Danish app used for fast money transfers.

We used a money-earlier-or-later task (Epper et al., 2020) with 16 choice situations to elicit time preferences. Panel (a) of Appendix Figure A1 shows a screenshot of one of the choice situations in the time task. In this choice situation, an individual could choose to get DKK 250 paid in 8 weeks or to save all or some of the money for later and receive the savings plus an interest rate of 2.4 percent in 16 weeks. In this example, the individual chose to save DKK 100 corresponding to saving 40 percent of the endowment (100/250). This gave a payout of DKK 150 in 8 weeks and a payout of DKK 102.4 in 16 weeks. The rate of return and the time profile varied across the choice situations (see Appendix Table A1). We compute the mean savings rate across the choice situations of each individual and then use this measure to rank people on a scale of 1 to 100, corresponding to their percentile positions in the distribution of elicited patience. Panel (a) of Appendix Figure A2 shows the distribution of the mean savings rate.

The elicitation of risk preferences is based on an investment task (Gneezy and Potters, 1997) with 15 choice situations. Panel (b) of Appendix Figure A1 shows a screenshot for one of the situations. Here, an individual can choose to get DKK 250 with certainty or invest some or all of the money in a lottery that yields an expected rate of return of 6 percent, with the risk of a significant loss. In this example, the individual chose to keep DKK 50 and invest DKK 200 in the lottery, which corresponds to an investment of 80 percent of the initial endowment of DKK 250. The investment gives DKK 80 (a loss) with a probability of 40 percent and DKK 300 (a win) with a probability of 60 percent. The outcome of the lottery and the sum of money earned were displayed afterwards. The probability of winning and the expected rate of return varied across the choice situations (see Appendix Table A2). Similarly to the measurement of patience, for each individual, we compute the mean amount not invested across the choice situations and then use this measure to rank people, thus obtaining their percentile position in the distribution of risk aversion. Panel (b) of Appendix Figure A2 shows the distribution of the mean keeping rate.

3.2 Data from administrative records

We link the experimental data to administrative records of the participants. We make use of several different registries, including:

- UDFK: Register including grades from the 9th grade to construct the GPA rank.
- KOT: Complete register over applications and admissions to higher education programs.

- UDDA: Completed education registry including information on whether participants obtained an upper secondary school degree.
- BEF: Population registry with information on gender, immigrant/descendant status, and link to parents.

We use the link to parents to include information on parental education (UDDA) and total income from the income tax registry (IND).

Participants in the experiment Our experimental sample consists of 4,415 individuals. We focus on individuals who have completed upper secondary school which is a requirement for admission to most programs in KOT. Specifically, we consider individuals who had completed upper secondary school between 2017 and 2022 (almost 90 percent graduate in 2018 and 2019). This results in 3,640 individuals (out of 4,415). In addition, we restrict ourselves to programs to which at least 10 participants apply to (resulting in 3,278 individuals). Finally, we drop individuals for whom we do not observe the grade point average in lower secondary school. This yields a final sample of 3,132 individuals, applying to 76 different programs, including 4 upper secondary school tracks. The last restriction is imposed because we use the grade point average as our proxy for cognitive skills. We use grades from the written final exams in Danish (reading, spelling, writing) and Math. Panel (c) of Appendix Figure A2 shows the distribution of grade point averages (grades in the Danish system are on a 7-point scale: -3, 0, 2, 4, 7, 10, 12). Just as we do for patience and risk aversion, we rank the individuals, thereby obtaining their percentile positions in the distribution of grade point average.

Background characteristics Panels A and B of Table 2 show the background characteristics. The first two columns show the statistics for the full population of Danes born in 1999 who completed upper secondary school and for whom we observe the lower secondary grade point average in the UDFK register. A random sample of 20 percent of the population was invited to participate in the experiments. The next two columns show the statistics for the analysis sample, while the last column shows the difference in the means between the sample and the population. The economic magnitude of the differences in background characteristics is small.

Characteristics of the applied-for program For those who apply to an educational program through the Coordinated Admission System, we define each applicant's applied-for program as their first priority program in the first year in which they apply. Therefore, this may not be the program to which they are admitted or the program they complete; in our sample, the share

Table 2: Descriptive statistics

	All		Sample		Difference
	Mean	Std. dev.	Mean	Std. dev.	
Panel A: Characteristics					
Male (=1)	0.45	0.50	0.48	0.50	0.03
Immigrant/descendant (=1)	0.10	0.30	0.09	0.29	-0.01
Apply in KOT (=1)	0.79	0.41	0.79	0.41	0.00
GPA in lower secondary school	7.67	2.23	8.14	2.19	0.48
Panel B: Parental background					
Father edu.: High (=1)	0.14	0.35	0.16	0.36	0.02
Father edu.: Medium (=1)	0.24	0.43	0.24	0.43	0.00
Father edu.: Low (=1)	0.62	0.49	0.60	0.49	-0.02
Mother edu.: High (=1)	0.13	0.34	0.14	0.35	0.01
Mother edu.: Medium (=1)	0.35	0.48	0.35	0.48	-0.00
Mother edu.: Low (=1)	0.52	0.50	0.51	0.50	-0.01
Income rank of father	55.39	28.02	56.16	27.65	0.76
Income rank of mother	55.75	28.23	56.44	27.99	0.69
Panel C: Applied-for program					
Log median earnings	13.09	0.28	13.14	0.28	0.04
Years of education	3.33	1.99	3.46	2.01	0.12
Earnings growth (%)	8.02	2.75	8.35	2.81	0.33
Risk of low earnings (%)	10.71	9.47	9.90	9.16	-0.81
Normalized IQR of earnings (%)	54.83	33.12	54.07	30.60	-0.76
Observations	43970		3132		

Notes: All includes all Danes born in 1999 who completed upper secondary school for whom we observe their grade point average from lower secondary school (63 percent of the 1999 cohort). A 20 percent random sample of the population was invited to participate in the online experiments. *Sample* is those who participated in the experiment, and apply for a program which at least 10 other participants also apply for. *Difference* is the difference between the sample mean and the population mean. *Male* and *Immigrant/descendant* are indicators for gender and immigrant status based on the population registry. *Apply in KOT* is an indicator that equals one if we observe an application for the individual in the KOT system. *GPA in lower secondary school* is the grade point average in written final exams in Danish and Math. Parental education levels are based on the Danish ISCED classification. *High* is Master's and PhD degrees, *Medium* is short- and medium-cycle higher education and Bachelor's degrees, and *Low* is lower secondary, upper secondary, and vocational education and training. The parental income ranks are the percentile ranks in the distribution of total income within all fathers/mothers of individuals born in 1999. *Log median earnings* is the log of median earnings in 2019 among graduates from the program. *Years of education* is the number of years of full-time study required to graduate from the program. *Earnings growth* is the annual growth rate of mean earnings from age 20 to age 42-47 for graduates from the program. *Risk of low earnings* is the probability that a graduate from the program has earnings in the bottom quintile of the earnings distribution in 2019. *Normalized IQR of earnings* is the inter-quartile range of earnings in 2019 among graduates from the program. The inter-quartile range is normalized by the median earnings and multiplied by 100.

of applicants admitted to their first priority program is 74 percent, similar to the share in the population. For applicants to academic bachelor's degrees, we link the bachelor's degree to the master's degree that the majority of previous students subsequently enroll in, since only a small share of students end their studies after completing the bachelor's degree.

We characterize each program by its length, that is, the additional years of study required to graduate, after secondary school, and its labor market outcomes. We use a reference sample consisting of individuals born during the period 1975-80 (approximately 330,000 individuals) to calculate program-specific earnings statistics, based on the graduates from each program (that is, by highest completed education by January 1st, 2019). We compute expected earnings growth for each program by first calculating mean earnings (in 2019 levels) at each age from 20 to 42–47 (depending on how long each cohort is observed in the data) for program graduates. By averaging at the program-by-age level, we avoid zero earnings observations. We then regress log mean earnings on age, and the estimated slope gives us the annual earnings growth rate for each program. To measure the variability of earnings that our experimental participants can expect to be faced with, we compute the risk of low earnings (tail risk) and the inter-quartile range of earnings (dispersion) for each program. Both measures are based on the earnings of graduates in 2019. We define low earnings as earnings in the bottom quintile of the earnings distribution among everyone in the reference sample. For each program, we thus compute the share of graduates with earnings in the bottom quintile. For the inter-quartile range, we compute the difference between $p(75)$ and $p(25)$ of earnings for each program and normalize it by the median earnings, $p(50)$, to get a measure of relative dispersion. Finally, we also compute the log of the median earnings, as a measure of the level of earnings for each program.

Appendix Table A3 shows the characteristics of the 20 largest educational programs. There is a fair amount of variation across programs. The economics program, for example, requires five years of study, has high annual earnings growth (11.5 percent), and a low risk of low earnings (3.4 percent). In contrast, the physiotherapist program is three years long, has modest earnings growth (6.3 percent), and a higher risk of low earnings (7.1 percent).

Panel C of Table 2 shows the descriptive statistics for the main outcomes we study. The individuals in the sample tend to apply to programs with slightly longer duration, higher earnings growth, and lower downside risk and volatility. However, the differences are small in economic terms. Overall, our analysis sample is quite similar to the population in terms of both background characteristics and key outcome variables.

Relationships between variables Before proceeding with the analysis, it is useful to summarize the relationships between the various variables. Appendix Table A4 shows the pairwise correlations between all the outcomes and explanatory variables. Several patterns stand out. First, GPA rank is positively correlated with both the patience and risk aversion ranks. Second, patience rank and risk aversion rank are negatively correlated. Third, programs with longer durations tend to have higher median earnings and earnings growth, but lower unemployment and earnings risk/volatility. Our preference measures and GPA rank also vary systematically by demographic characteristics (see Appendix Table A5). For example, males tend to have lower patience ranks and GPAs. Likewise, individuals with more educated parents tend to have higher patience and GPA ranks. However, these characteristics jointly explain less than 5 percent of the variation in patience and risk aversion ranks.

4 Results

We now turn to the empirical investigation of the hypotheses outlined in Table 1. We conduct the analysis at the program level, since the relevant outcome variation is at that level. In this setting, the identifying variation is between programs, and estimation is therefore driven by between-program differences rather than within-program individual variation (Angrist and Pischke, 2009). Accordingly, regressors are constructed as program-level averages of individual characteristics.[1]

Specifically, we proceed as follows. We rank the 3,132 participants from 1 to 100 according to their percentile position in the distributions of experimental choices and grade point average. We then compute the average rank of applicants—in terms of risk aversion, patience, and grade point average—to each study program, such as Economics.

Figure 1 plots the bivariate relationship between average applicant preferences and program outcomes. Each circle in each of the panels represents one of the 76 programs, with the x-axis showing the average patience or risk aversion of the applicants to the program. The y-axis reports program characteristics—such as duration or labor market outcomes of past graduates. Red lines show fitted values from ordinary least squares regressions of each outcome on the corresponding average preference rank. All regressions are estimated at the program level and weighted by the number of applicants using frequency weights.

Consistent with the hypotheses in Table 1, patience rank is positively associated with program duration and earnings growth (Panels a and b). The estimated slopes suggest that moving up 10 percentiles in the distribution of patience on average is associated with almost one-and-a-half years of additional education and an increase of 2.4 percentage points in annual earnings growth. Similarly, in line with the hypotheses, Panels c and d show a negative relationship between risk aversion rank and earnings risk/volatility. Here, the estimated slopes suggest that moving up 10 percentiles in the distribution of risk aversion on average is associated with a reduction in low earnings risk of 6.2 percentage points (which is more than 60 percent of the average sample probability of 9.9 percent) and a reduction in the normalized inter-quartile range of around 16 percentage points (of the median earnings).

[1] Appendix Table A6 presents results from a specification that uses individual-level regressors rather than program-level averages. The estimates are qualitatively similar but smaller in magnitude than those reported in Table 3. This pattern reflects that the grouped specification focuses on between-program variation, whereas the individual-level specification also incorporates within-program individual variation that does not contribute to explaining between-program differences in the outcome.

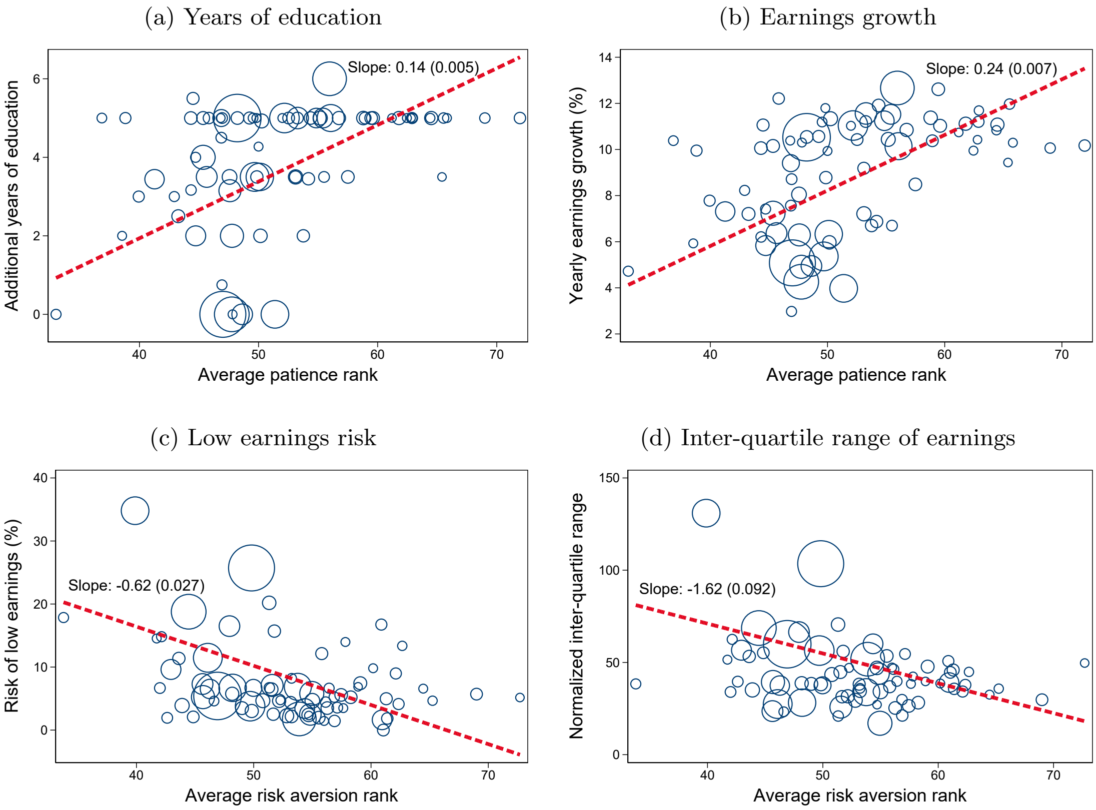

Figure 1: Association between preferences and education and labor market outcomes

Notes: Each scatter represents an educational program. The size of the scatters reflects the number of participants applying for the program. On the x-axis we plot the average preference rank among the participants who applied for the program. On the y-axis we plot the program outcomes. For years of education, it is the average number of years studying full time required to graduate from the program. The labor market outcomes are based on the actual outcomes of graduates from the programs. The red line illustrates the ordinary least squares prediction from a regression of the outcome on the preference at the program level, but with frequency weights. In Panel (d), we do not show two outlier observations with normalized inter-quartile ranges of more than 180 and 250, respectively. We include the observations in all estimations. $N = 3,132$. Robust standard errors in parentheses.

Table 3 reports regressions of each outcome in Figure 1 on preference measures and GPA rank. For each outcome, we present both simple bivariate estimates and multivariable regression specifications with and without controls. Column 3 (6), for example, shows that patience and risk aversion ranks are positively associated with program length (earnings growth), even conditional on GPA rank and controls. Theory predicts a positive relationship between patience and the outcomes in Panel A.[2] In terms of magnitudes, the coefficient on patience rank is approximately one-quarter (one-sixth) of the GPA rank coefficient for program duration (earnings growth). This indicates that sorting across programs reflects not only ability, but also economic preferences.

Consistent with theory, Panel B of Table 3 shows that more risk-averse individuals sort into programs with a lower likelihood of low earnings and smaller inter-quartile earnings dispersion.

[2]Theoretically, the relationship between risk preferences and years of education or earnings growth is not clear. Here, we see a positive relationship between risk aversion and these outcomes. We suspect this is because these outcomes are highly negatively correlated with tail risk and dispersion (Appendix Table A4).

Table 3: Regressions of education and labor market outcomes on preferences

	Additional years of education			Earnings growth (%)		
	(1) Bivar.	(2) Multi.	(3) Multi.	(4) Bivar.	(5) Multi.	(6) Multi.
Panel A						
Average patience rank	0.14	0.021	0.019	0.24	0.024	0.023
	(0.0046)	(0.0037)	(0.0046)	(0.0069)	(0.0051)	(0.0059)
Average risk aversion rank	0.17	0.024	0.050	0.28	0.012	0.043
	(0.0048)	(0.0040)	(0.0042)	(0.0067)	(0.0054)	(0.0049)
Average GPA rank	0.095	0.085	0.074	0.17	0.16	0.14
	(0.0015)	(0.0021)	(0.0029)	(0.0014)	(0.0020)	(0.0032)
R^2		0.516	0.674		0.795	0.848
Mean outcome	3.46	3.46	3.46	8.35	8.35	8.35
	Low earnings (%)			Inter-quartile range (%)		
	(7) Bivar.	(8) Multi.	(9) Multi.	(10) Bivar.	(11) Multi.	(12) Multi.
Panel B						
Average patience rank	-0.54	-0.10	-0.21	-1.27	-0.66	-1.09
	(0.028)	(0.030)	(0.033)	(0.13)	(0.14)	(0.17)
Average risk aversion rank	-0.62	-0.085	-0.30	-1.62	-1.13	-1.42
	(0.027)	(0.034)	(0.032)	(0.092)	(0.18)	(0.16)
Average GPA rank	-0.34	-0.30	-0.32	-0.55	-0.16	-0.69
	(0.011)	(0.015)	(0.020)	(0.050)	(0.070)	(0.10)
R^2		0.327	0.508		0.114	0.278
Mean outcome	9.90	9.90	9.90	54.1	54.1	54.1
Observations	3132	3132	3132	3132	3132	3132
# programs	76	76	76	76	76	76
Controls			✓			✓

Notes: The table shows coefficients from ordinary least squares regressions of outcomes on preferences and grade point average. Regressions are at the program level, weighted by the number of applicants. Columns 1, 4, 7, and 10 are bivariate regressions, i.e., each outcome is regressed on one explanatory variable at a time. Remaining columns show results from multivariable regressions. *Controls* include program-level shares of males, immigrants and descendants of immigrants, and students with no highly educated parents, as well as the program-average income rank of fathers and mothers. Robust standard errors in parentheses.

We also see that students with higher ability sort into programs with lower earnings risk/volatility. However, the estimates in columns (9) and (12) suggest that risk preferences play a role comparable to, and in some cases larger than, GPA rank in shaping program choice.

The fact that there is ability sorting into fields is not a new observation. However, the patterns in Figure 1 and Table 3 clearly indicate that individuals also sort into programs based on their economic preferences. Overall, the predictive power of time and risk preferences is substantial relative to traditional predictors such as grade point average, suggesting that experimentally elicited preferences capture economically meaningful heterogeneity in educational choices.

Robustness checks We conduct a series of additional analyses to assess the robustness of our results.

Because the explanatory variables differ in their underlying variation, we standardize them and use z-scores instead of ranks. Appendix Figure A3 and Panel A of Appendix Table A7 correspond to Figure 1 and Table 3, respectively. Our qualitative conclusions are unchanged using these z-scores.

The lower panel of Appendix Table A7 reports results using structurally estimated discount rate and risk aversion parameters, rather than the experimental choices directly. Again, the results are qualitatively similar.

We have focused on outcomes that most directly operationalize the theoretical predictions. Nevertheless, one may be interested in how the preference measures relate to the level of program earnings. This is examined in Appendix Table A8, where the outcome variables are the *level* of earnings rather than the growth rate, and unemployment risk rather than the risk of low earnings and earnings dispersion. We compute the level of earnings as the log of the median earnings in 2019 for graduates from each program in the reference sample (the 330,000 people born 1975-80). To avoid earnings fluctuations affecting our measure of the median earnings, we also show a specification where the median earnings are based on individual average earnings over a 5-year period. We define unemployment as having been unemployed for more than 3 months in a calendar year. Our unemployment measure is thus the share of graduates from a program who experienced more than 3 months of unemployment in 2019. Since unemployment is a low-frequency outcome in the reference sample (around 2 percent), we also show a specification where we measure unemployment over a five-year period, that is, the unemployment indicator equals one if an individual was unemployed for more than 3 months in a calendar year between 2015 and 2019. From a theoretical perspective, the relationship between preferences and earnings levels is ambiguous. However, we would expect programs with higher unemployment risk to attract individuals who are less risk averse. Consistent with this prediction, Appendix Table A8 shows that programs with higher unemployment risk do attract applicants with lower risk aversion ranks.

5 Conclusion

This paper shows that elicited economic preference parameters among young individuals have substantial predictive power for subsequent post-secondary educational choices, even after controlling for cognitive ability and parental background, consistent with the predictions of human capital theory.

Although our results are consistent with the theoretical predictions, we cannot identify a causal relationship, as doing so would require random assignment of inherent personal characteristics. A further challenge is that preferences are latent individual characteristics and are therefore not directly observable. Experimental elicitation relies on a self-revelation mechanism in a concrete choice context to measure the key preference parameters. Importantly, however, our results rely only on the experiment's ability to identify who is more or less patient and risk averse than others. They are therefore independent of the exact values of the preference parameters elicited in the experiment, as long as the ranking of individuals is preserved. Taking these considerations into account, we believe our approach comes as close as possible to an empirical test of the theory.

Our results carry significant implications for understanding human capital formation and educational inequality. The predictive power of preferences suggests that explanations focusing solely on ability or financial constraints may miss important dimensions of heterogeneity in educational investment decisions.

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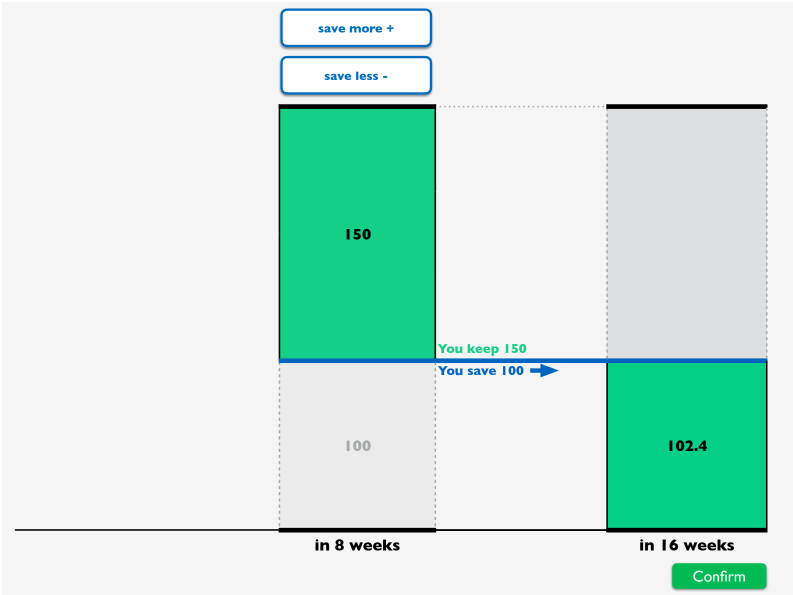
Appendix

(a) Time



(b) Risk

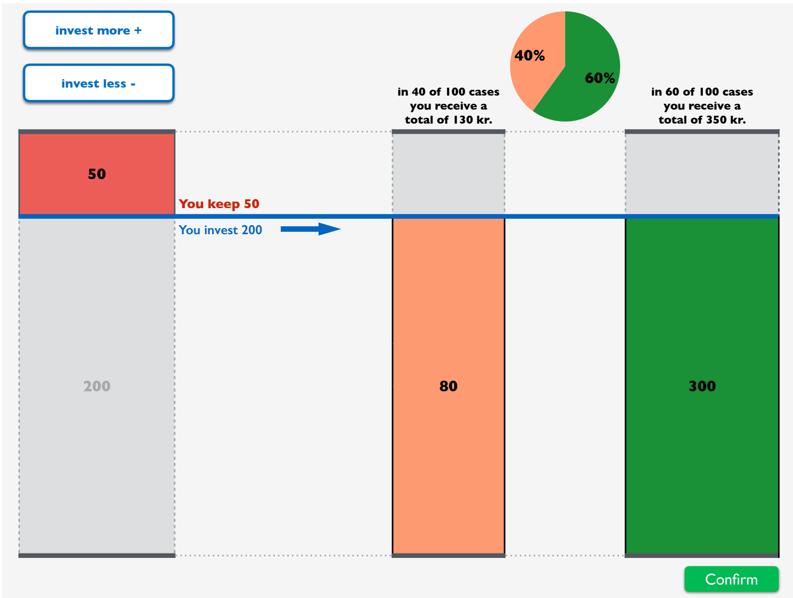
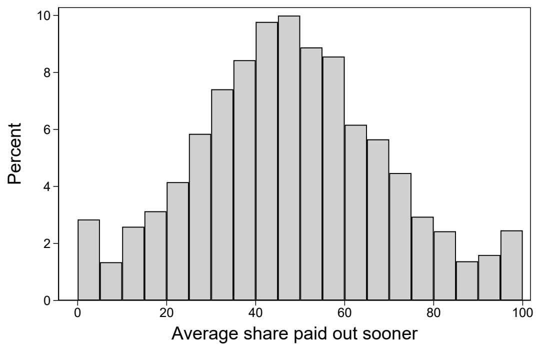


Figure A1: Screenshots of online experiment eliciting time and risk preferences

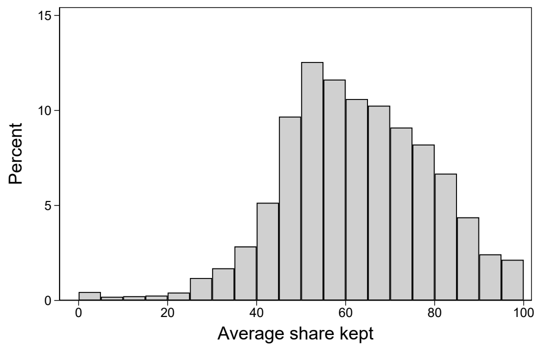
Notes: Panel (a) shows an example of a choice situation used to elicit time preference. The participant can choose how much of 250 DKK to receive in 8 weeks, and how much to save with interest to be paid out in 16 weeks. In the example, the participant keeps 150 and saves 100. The participant thus receives 150 DKK in 8 weeks and 102.4 DKK ($100 \times (1 + 0.024)$) in 16 weeks. Panel (b) shows an example of a choice situation used to elicit risk preference. The participant can choose how much of 250 DKK to keep in a safe account, and how much to invest in a risky lottery with a 40 percent probability of loss and a 60 percent probability of gain. In the example, the participant keeps 50 and invests 200. With 40% probability, the participant receives 130 DKK (50 + 80), and with 60% probability, the participant receives 350 DKK (50 + 300). See all choice situations in Appendix Tables A1 and A2.

Figure A2: Distributions of explanatory variables

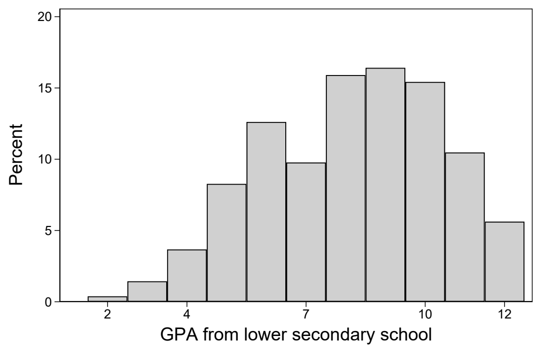
(a) (Im)patience



(b) Risk aversion

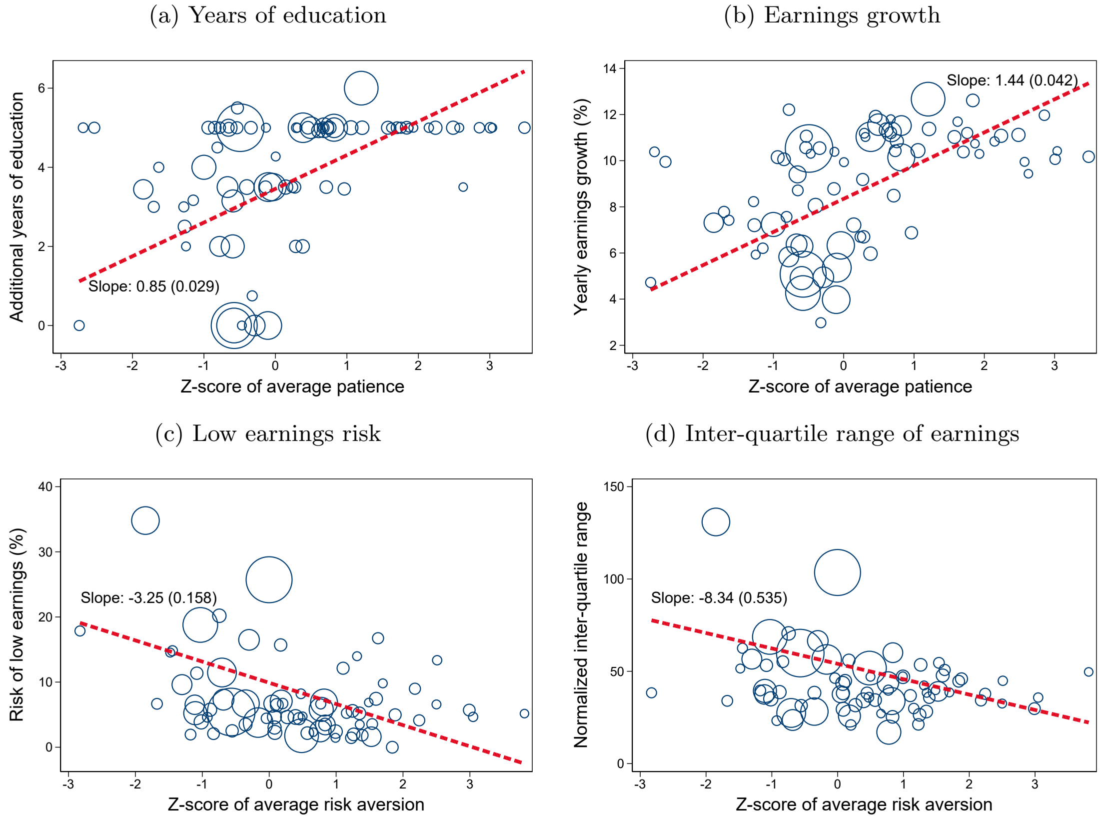


(c) Grade point average



Notes: Panels (a) and (b) show the distributions of the average choices in the experiments for each participant across all choice situations. Panel (c) shows the distribution of the grade point average in Danish and Math from the final written exams in lower secondary school. $N = 3,132$.

Figure A3: Z-scores of economic preferences and education and labor market outcomes



Notes: The figure is similar to Figure 1, but instead of using ranks within the distribution of preferences we use z-scores. We compute the program z-scores as follows. For the 3,132 participants, we use the average shares paid out and kept in the experiments and the GPA from lower secondary school. We then compute the applied-for program means of these three variables. Finally, we standardize the applied-for program means using the 3,132 observations to compute the mean and standard deviation. Each scatter represents an educational program. The size of the scatters reflects the number of participants applying for the program. On the x-axis we plot the program z-scores. On the y-axis we plot the program outcomes. For years of education, it is the average number of years studying full time required to graduate from the program. The labor market outcomes are based on the actual outcomes of graduates from the programs. The red line illustrates the ordinary least squares prediction from a regression of the outcome on the z-score at the program level, using frequency weights. In Panel (d), we do not show two outlier observations with normalized inter-quartile ranges of more than 180 and 250, respectively. We include the observations in all estimations. $N = 3,132$. Robust standard errors in parentheses.

Table A1: Choice situations in the time experiment

	Low stakes		High stakes				
Situation	x_1	x_2	x_1	x_2	t_1	t_2	Rate
1	250	251	7500	7530	0	8	0.024
2	250	256	7500	7680	0	8	0.153
3	250	261	7500	7830	0	8	0.295
4	250	266	7500	7980	0	8	0.451
5	250	271	7500	8130	0	8	0.622
6	250	276	7500	8280	0	8	0.811
7	250	281	7500	8430	0	8	1.016
8	250	286	7500	8580	0	8	1.242
9	250	251	7500	7530	8	16	0.024
10	250	256	7500	7680	8	16	0.153
11	250	261	7500	7830	8	16	0.295
12	250	266	7500	7980	8	16	0.451
13	250	271	7500	8130	8	16	0.622
14	250	276	7500	8280	8	16	0.811
15	250	281	7500	8430	8	16	1.016
16	250	286	7500	8580	8	16	1.242

Notes: x_1 is the amount the participant can get paid out sooner and x_2 is the amount the participant can get paid out later. They differ by whether the participant was assigned to the low or high stakes treatment. t_1 indicates the sooner payout time (either within 24 hours (0) or in 2 months) while t_2 indicates the later payout time (either in 8 weeks or in 16 weeks). The user interface displayed the delays in weeks to avoid confounds by payments at different weekdays. Rate is the annualized interest rate the participant gets on the amount saved for two months. For instance, in Situation 1, Rate=0.024 refers to a annual interest rate of 2.4%. Panel (a) of Appendix Figure A1 illustrates situation 9 with low stakes.

Table A2: Choice situations in the risk experiment

Situation	DKK	p	Good	Bad
1	250	0.5	1.21	0.81
2	250	0.2	1.41	0.91
3	250	0.8	1.11	0.61
4	250	0.5	1.31	0.71
5	250	0.2	1.61	0.86
6	250	0.8	1.16	0.41
7	250	0.5	1.35	0.75
8	250	0.2	1.65	0.90
9	250	0.8	1.20	0.45
10	250	0.6	1.50	0.40
11	250	0.4	1.72	0.62
12	250	0.6	1.45	0.35
13	250	0.4	1.67	0.57
14	250	0.5	1.51	0.50
15	250	0.5	1.61	0.60

Notes: *DKK* is the amount the participant can keep or invest in the lottery. p is the probability that the lottery will give the good state. *Good* is the rate of return of the investment in the good state while *Bad* is the rate of return of the investment in the bad state. Panel (b) of Appendix Figure A1 illustrates situation 10.

Table A3: Examples of education programs

Program	Obs.	Years	Earnings	Growth	Low	IQR
USS: General	293	0	12.8	5.1	25.7	103.5
USS: Preparatory	106	0	12.6	4	34.8	130.9
USS: Commercial	167	0	12.9	4.3	18.8	68.6
USS: Technical	59	0	13	4.9	16.5	66.5
AP in Financial management	74	2	13.1	4.9	5.2	39.4
AP in Marketing management	55	2	13	5.8	9.6	56.6
Physiotherapist	67	3	12.9	6.3	7.1	25.8
Professional BA in finance	52	3.5	13.2	7.3	6.5	37.5
Social educator	115	3.5	12.8	5.4	11.5	27.4
Social worker	60	3.5	12.9	6.4	7.3	23.6
Nurse	104	3.5	12.9	6.3	6.7	28.2
Teacher	80	4	13	7.2	5.8	17
Communication	40	5	13.1	9.4	6.7	37.6
Data science	53	5	13.4	11.2	1.6	39.1
Law	121	5	13.4	11	3.8	56.4
Political science	64	5	13.4	11.6	2.5	43.9
Psychology	101	5	13.1	10.1	6.9	33.9
Economics	54	5	13.5	11.5	3.4	60.1
Business economics	313	5	13.4	10.5	5.4	59.9
Medicine	157	6	13.6	12.7	1.8	51.8

Notes: The table shows the main outcomes for the 20 largest educational programs in terms of number of applicants among the participants in the experiments. USS is an abbreviation for Upper Secondary School. AP is an abbreviation for Academy Profession. *Obs.* is the number of participants we observe applying for the program among the sample of 3,132. *Years* is the number of years of full time study required to graduate from the program. *Earnings* is the log of median earnings in 2019 among graduates from the program. *Growth* is the annual growth rate of mean earnings from age 20 to age 42-47 for graduates from the program. *Low* is the probability that a graduate from the program has earnings in the bottom quintile of the earnings distribution in 2019. *IQR* is the inter-quartile range of earnings in 2019 among graduates from the program. The inter-quartile range is normalized by the median earnings and multiplied by 100.

Table A4: Pairwise correlations

	Pairwise correlations								
	1.	2.	3.	4.	5.	6.	7.	8.	9.
Explanatory variables									
1. Patience rank	1.00	-0.13	0.15	0.08	0.09	-0.05	-0.07	0.08	-0.07
2. Risk aversion rank	-0.13	1.00	0.13	0.10	0.11	-0.06	-0.08	0.07	-0.05
3. GPA rank	0.15	0.13	1.00	0.37	0.47	-0.14	-0.30	0.41	-0.21
Main outcomes									
4. Additional years	0.08	0.10	0.37	1.00	0.90	-0.64	-0.86	0.79	-0.57
5. Earnings growth	0.09	0.11	0.47	0.90	1.00	-0.37	-0.71	0.86	-0.52
6. Inter-quartile range	-0.05	-0.06	-0.14	-0.64	-0.37	1.00	0.84	-0.46	0.53
7. Low earnings risk	-0.07	-0.08	-0.30	-0.86	-0.71	0.84	1.00	-0.82	0.73
Additional outcomes									
8. Log median earnings	0.08	0.07	0.41	0.79	0.86	-0.46	-0.82	1.00	-0.66
9. Unemployment	-0.07	-0.05	-0.21	-0.57	-0.52	0.53	0.73	-0.66	1.00

Notes: The table shows the pairwise correlations at the individual level. *Patience rank* is the individual rank in the distribution of average share paid out later in the time experiment. *Risk aversion rank* is the individual rank in the distribution of the average share not invested in the risky lottery in the risk experiment. *GPA rank* is the individual rank in the distribution of grade point average in the final written exams in Danish and Math in lower secondary school. *Additional years* is the number of years of full time study required to graduate from the applied-for program. *Earnings growth* is the annual growth rate of mean earnings from age 20 to age 42-47 for graduates from the applied-for program. *Low* is the probability that a graduate from the program has earnings in the bottom quintile of the earnings distribution in 2019. *Inter-quartile range* is the inter-quartile range of earnings in 2019 among graduates from the applied-for program. The inter-quartile range is normalized by the median earnings. *Log median earnings* is the log of median earnings in 2019 among graduates from the applied-for program. *Unemployment* is the probability that a graduate from the applied-for program was unemployed for more than 3 months in a calendar year between 2015 and 2019. $N = 3,132$.

Table A5: Preferences, GPA, and background characteristics

	Patience rank		Risk aversion rank		GPA rank	
	(1) Bivar.	(2) Multi.	(3) Bivar.	(4) Multi.	(5) Bivar.	(6) Multi.
Male (=1)	-8.62	-8.90	-0.67	-0.84	-3.32	-4.44
	(1.01)	(1.03)	(1.02)	(1.04)	(1.01)	(0.97)
Immigrant/descendant (=1)	-6.82	-4.76	-3.03	-1.92	-16.64	-9.77
	(1.34)	(1.89)	(1.36)	(1.96)	(1.31)	(1.77)
Father edu.: High (=1)	3.29	1.57	2.26	-0.08	19.45	11.18
	(1.19)	(1.58)	(1.19)	(1.61)	(1.13)	(1.45)
Mother edu.: High (=1)	3.49	1.43	5.70	4.93	19.39	10.22
	(1.21)	(1.66)	(1.21)	(1.67)	(1.18)	(1.54)
Income rank of father	0.04	0.02	0.02	-0.00	0.22	0.11
	(0.14)	(0.02)	(0.14)	(0.02)	(0.13)	(0.02)
Income rank of mother	0.06	0.04	0.05	0.03	0.21	0.09
	(0.14)	(0.02)	(0.14)	(0.02)	(0.13)	(0.02)
Observations		3132		3132		3132
R^2		0.031		0.006		0.124
Mean outcome		50.5		50.5		50.5

Notes: The table shows coefficients from ordinary least squares regressions of preferences and grade point average on background characteristics. Regressions are at the individual level. Columns 1, 3, and 5 are bivariate regressions, i.e., each outcome is regressed on one explanatory variable at a time. Remaining columns show results from multivariable regressions. *Patience rank* is the individual rank in the distribution of average share paid out later in the time experiment. *Risk aversion rank* is the individual rank in the distribution of the average share not invested in the risky lottery in the risk experiment. *GPA rank* is the individual rank in the distribution of grade point average in the final written exams in Danish and Math in lower secondary school. *Male* and *Immigrant/descendant* are indicators for gender and immigrant status. *Father/mother edu.: High* are indicators for parents having obtained Master's or PhD degrees. The parental income ranks are the percentile ranks in the distribution of total income within all fathers/mothers to individuals born in 1999. Robust standard errors in parentheses.

Table A6: Individual level regressions

	Additional years of education			Earnings growth (%)		
	(1) Bivar.	(2) Multi.	(3) Multi.	(4) Bivar.	(5) Multi.	(6) Multi.
Patience rank	0.0055	0.0023	0.0017	0.0093	0.0034	0.0039
	(0.0012)	(0.0012)	(0.0012)	(0.0017)	(0.0016)	(0.0016)
Risk aversion rank	0.0067	0.0037	0.0036	0.011	0.0057	0.0058
	(0.0013)	(0.0012)	(0.0012)	(0.0017)	(0.0016)	(0.0015)
GPA rank	0.026	0.025	0.024	0.046	0.044	0.042
	(0.0011)	(0.0011)	(0.0012)	(0.0014)	(0.0014)	(0.0015)
R^2		0.144	0.179		0.222	0.259
Mean outcome	3.46	3.46	3.46	8.35	8.35	8.35
	Low earnings (%)			Inter-quartile range (%)		
	(7) Bivar.	(8) Multi.	(9) Multi.	(10) Bivar.	(11) Multi.	(12) Multi.
Patience rank	-0.021	-0.0090	-0.0096	-0.049	-0.034	-0.022
	(0.0057)	(0.0056)	(0.0056)	(0.020)	(0.020)	(0.020)
Risk aversion rank	-0.024	-0.014	-0.014	-0.063	-0.049	-0.048
	(0.0057)	(0.0055)	(0.0054)	(0.019)	(0.019)	(0.018)
GPA rank	-0.094	-0.091	-0.090	-0.15	-0.14	-0.14
	(0.0057)	(0.0058)	(0.0061)	(0.021)	(0.021)	(0.022)
R^2		0.091	0.115		0.023	0.037
Mean outcome	9.90	9.90	9.90	54.1	54.1	54.1
Observations	3132	3132	3132	3132	3132	3132
Controls			✓			✓

Notes: The table is similar to Table 3, but instead of using frequency weighted groups as the level of observation, we use individual observations. The table shows coefficients from ordinary least squares regressions of outcomes on preferences and grade point average. Columns 1, 4, 7, and 10 are bivariate regressions, i.e., each outcome is regressed on one explanatory variable at a time. Remaining columns show results from multivariable regressions. *Controls* include indicators of males, immigrants and descendants of immigrants, and students with no highly educated parents, as well as the income rank of fathers and mothers. Robust standard errors in parentheses.

Table A7: Alternative measures of preferences

	Years of education		Earnings growth (%)		Low earnings (%)		Inter-quartile range (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bivar.	Multi.	Bivar.	Multi.	Bivar.	Multi.	Bivar.	Multi.
Panel A: Z-scores								
Average patience (z-score)	0.85	0.093	1.44	0.16	-3.18	-1.10	-7.20	-5.73
	(0.029)	(0.027)	(0.042)	(0.034)	(0.15)	(0.17)	(0.70)	(0.84)
Average risk aversion (z-score)	0.94	0.24	1.55	0.23	-3.25	-1.32	-8.34	-6.32
	(0.026)	(0.025)	(0.036)	(0.028)	(0.16)	(0.19)	(0.54)	(0.91)
Average GPA (z-score)	1.43	1.14	2.49	2.08	-5.33	-5.40	-8.78	-13.3
	(0.023)	(0.044)	(0.023)	(0.049)	(0.17)	(0.30)	(0.80)	(1.67)
R^2		0.670		0.845		0.513		0.272
Panel B: Structural parameters								
Average patience rank	0.12	0.022	0.17	0.016	-0.44	-0.22	-1.58	-1.27
	(0.0052)	(0.0049)	(0.0071)	(0.0063)	(0.036)	(0.035)	(0.16)	(0.18)
Average risk aversion rank	0.16	0.024	0.27	0.026	-0.53	-0.15	-1.45	-1.16
	(0.0047)	(0.0043)	(0.0069)	(0.0053)	(0.024)	(0.028)	(0.074)	(0.11)
Average GPA rank	0.095	0.081	0.17	0.14	-0.34	-0.36	-0.55	-0.81
	(0.0015)	(0.0033)	(0.0014)	(0.0036)	(0.011)	(0.019)	(0.050)	(0.090)
R^2		0.666		0.845		0.495		0.275
Observations	3132	3132	3132	3132	3132	3132	3132	3132
# programs	76	76	76	76	76	76	76	76
Controls		✓		✓		✓		✓
Mean outcome	3.46	3.46	8.35	8.35	9.90	9.90	54.1	54.1

Notes: In Panel A, we use z-scores of the choices in the experiments and grade point average. We compute the program z-scores as follows. For the 3,132 participants, we use the average shares paid out and kept in the experiments and the GPA from lower secondary school. We then compute the applied-for program means of these three variables. Finally, we standardize the applied-for program means using the 3,132 observations to compute the mean and standard deviation. In Panel B, we use structurally estimated preference parameters and then compute the ranks based on these instead of the choices directly. For more details on the structural estimation, see the supplementary information for Epper et al. (2022). The table shows coefficients from ordinary least squares regressions of outcomes on preferences and grade point average. Regressions are at the program level, weighted by the number of applicants. Columns 1, 3, 5, and 7 are bivariate regressions, i.e., each outcome is regressed on one explanatory variable at a time. Remaining columns show results from multivariable regressions. *Controls* include program-level shares of males, immigrants and descendants of immigrants, and students with no highly educated parents, as well as the program-average income rank of fathers and mothers. Robust standard errors in parentheses.

Table A8: Earnings and unemployment

	Log of median earnings		Unemployment > 3 m. (%)	
	(1)	(2)	(3)	(4)
	2019	2015-19	2019	2015-19
Average patience rank	0.0055	0.0033	-0.064	-0.22
	(0.00071)	(0.00053)	(0.0077)	(0.020)
Average risk aversion rank	-0.0014	-0.0027	-0.027	-0.10
	(0.00073)	(0.00059)	(0.0077)	(0.023)
Average GPA rank	0.014	0.012	-0.035	-0.11
	(0.00048)	(0.00037)	(0.0040)	(0.011)
R^2	0.806	0.840	0.303	0.347
Mean outcome	13.1	13.2	2.38	7.99
Observations	3132	3132	3132	3132
# programs	76	76	76	76
Controls	✓	✓	✓	✓

Notes: The table shows coefficients from ordinary least squares regressions of outcomes on preferences and grade point average. For *Log of median earnings*, we first compute the median earnings for graduates from each program—either using earnings in 2019 or average earnings from 2015 to 2019. We then compute the log of the median earnings. For *Unemployment ¿ 3 m.*, we use an indicator for being unemployed for more than 3 months—either in 2019 or in at least one year from 2015 to 2019. *Controls* include program-level shares of males, immigrants and descendants of immigrants, and students with no highly educated parents, as well as the program-average income rank of fathers and mothers. Robust standard errors in parentheses.