Using Childhood Skills to Forecast Lifecycle Outcomes

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Research Questions

- How predictive are the cognitive and non-cognitive skills measured at early childhood, relative to those measured at later ages?
- What is the best forecasting model based on childhood skill measures for each of adult outcome?
- How does the predictive power of skills vary across outcome distribution?

Method I

We address question one using simple OLS regression for the outcome, Y_i, on the inputs of θ^c, θ^{nc} controlling for the baseline characteristics of gender and race. We regress outcomes taken at ages 23, 33, 42, and 50 and using measures of skill taken at ages 6-8, 10-12, and 16.

We measure cognitive skill as being a single factor extracted from the normalized math and reading test scores for each age.

We construct measures of non-cognitive skill both as a single factor, and as and internalizing factor and externalizing factor based on the teachers report of child's behavioral problems in the classroom.

We consider labor market outcomes, including wages, hours worked, and duration of unemployment spells. We consider measured health outcomes, including self-perceived general health, obesity, and a binary indicator based on the Malaise index.

We estimate all combinations of skill and age of the form:

$$y_{i,33} = \alpha x_i + \beta\theta^C_7 + \beta\theta^{nc}_7 + \varepsilon_i \tag{1}$$

Method II

We address question two using receiver operator characteristic (ROC) analysis and using quantile regression

We measure cognitive and non-cognitive skill using the same factor methods as above.

ROC plots true positive rate vs. false positive rate, we show results by decile of outcome, using both cognitive and non-cognitive skill,, and measures how well each type of skill performs as a classifer, where each quantile of outcome represents one class.

Quantile regressions measure the contribution of cognitive and non-cognitive skill to the observed outcome:

Quantile regressions are of estimated of the form, where $q \in \{1, . . . , 10\}$:

$$y_{i,33}^{q_i = q} = \alpha x_i + \beta \theta_7^{c} + \beta \theta_7^{nc} + \varepsilon_i \tag{2}$$

Data

- Our analysis takes advantage of two nationally representative surveys with comparable outcome measures and measures of childhood skill.
    - National Childhood Development Survey, a sample of 17,415 men and women born during 1958 and followed through the current date.
    - The Children of the National Longitudinal Study of Youth (1979). A survey of the 11,521 children born to mothers who participated in the National Longitudinal Study of Youth as of 2014.
    - Our sample is restricted to only those participants for whom there exist at least two childhood measurements of skill and at least two periods of observable outcomes.

Data I – NCDS

- Sample of men and women born during one week in march of 1958
- Perinatal and family history data was collected from the parents during 1958 (original aim of study was to investigate perinatal mortality in the UK)
- Follow ups completed in 1965 (age 7); 1969 (age 11), 1974 (age 16), 1981, (age 23), 1991 (age 33), 2000 (age 42), 2004 (age 46), 2008 (age 50), 2013 (age 55), and an age 60 follow up scheduled for 2018. Supplemental surveys by mail (or phone) in 1978 (age 20) and 2002 (age 44).

Data II - NCDS

- The 1978 survey collected exam scores as the participants completed the secondary education and the 2002 survey collected biomedical data and cognitive skill measures
- During waves 1-3 (ages 6-16), individual ability was reported by both teachers and parents with identical questions. Academic performance, measures of general aptitude and specific ability were also rated by both teachers and parents.
- In wave 3, the individuals also self-reported measures of ability and academic performance. Both teachers and the individual were asked about their expectations for the individual with respect to the upcoming national exams.

Data I – CNLSY

- 11,521 children born to NLSY79 mothers as of 2014.

(5,882 males and 5,638 females)

- Born between 1970 and 2014. At the time of the first interview in 1986, child ages ranged from 0-23 years.
- Annual follow ups collected between 1987 and 1994, with biennial follow ups since 1994.

Data II - CNLSY

- The 1978 survey collected exam scores as the participants completed the secondary education and the 2002 survey collected biomedical data and cognitive skill measures
- Cognitive Skill measures include the Digit Span scale of the Wechsler, the Peabody Picture Vocabulary Test-Revised (PPVT-R), and the Peabody Individual Achievement Tests (PIAT) for math and reading
- Non-cognitive skill measures include Motor and Social Development reports and the Behavior Problems Index

Outcomes

Labor and earnings

- Log weekly earnings, tenure on job, avg. hours worked per week, number of years unemployed, professional skills)
- Classification by quintiles of earnings, hours worked, number of unemployment spells

Educational outcomes

- Educational attainment at 23 & 33, National exam scores (A / Higher levels, O levels, GSE), no. of years of schooling beyond age 16, continuing professional or vocational training
- Involvement in own child's education (wave 5, age 33) / Child's educational attainment (wave 7, age 46)

Health

- Body mass index, self reported general health, # of days hospitalized.
- Classification of obesity, malaise index indicator

Outcome & Skill Correlation - Males

Math + Reading Test, 7									
0.699	Math + Reading Test, 11								
0.654	0.824	Math + Reading Test , 16							
-0.132	-0.108	-0.115	Behavior Report, 7						
-0.149	-0.125	-0.150	0.460	Behavior Report, 11					
-0.132	-0.193	-0.291	0.050	0.087	Behavior Report, 16				
-0.287	-0.340	-0.363	0.112	0.162	0.236	Bristol Social Adj. Score, 11			
0.151	0.195	0.216	-0.056	-0.047	-0.063	-0.096	(log) - Weekly Gross Income		
0.433	0.560	0.640	-0.090	-0.092	-0.286	-0.254	0.210	Highest Level of Education	
-0.117	-0.163	-0.162	0.076	0.079	0.100	0.126	-0.056	-0.131	std. Malaise Index Score

Outcome & Skill Correlation - Females

Math + Reading Test, 7									
0.690	Math + Reading Test, 11								
0.626	0.794	Math + Reading Test , 16							
-0.102	-0.121	-0.149	Behavior Report, 7						
-0.140	-0.154	-0.191	0.464	Behavior Report, 11					
-0.132	-0.183	-0.302	0.088	0.102	Behavior Report, 16				
-0.286	-0.328	-0.335	0.133	0.151	0.234	Bristol Social Adj. Score, 11			
0.168	0.220	0.245	-0.058	-0.070	-0.070	-0.098	(log) - Weekly Gross Income		
0.402	0.533	0.620	-0.147	-0.153	-0.259	-0.255	0.290	Highest Level of Education	
-0.102	-0.141	-0.168	0.116	0.123	0.111	0.114	-0.081	-0.154	std. Malaise Index Score

NCDS – Q1 Income

main							
auc	0.409***	0.421***	0.421***	0.411***	0.413***	0.410***	0.409***
	(30.30)	(36.11)	(35.52)	(28.93)	(31.44)	(31.32)	(30.30)
ncogall_std							
auc	0.525***						0.525***
	(85.76)						(85.76)
ncog_std7							
auc		0.514***					
		(108.04)					
ncog_std11							
auc			0.514***				
			(99.88)				
ncog_std16							
auc				0.504***			
				(76.17)			
ncog_std7_11							
auc					0.521***		
					(102.11)		
ncog_std11_16							
auc						0.515***	
						(71.67)	
N	32935	64120	57690	56555	46265	40675	32935

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4

NCDS – Q5 Income

main							
auc	0.691***	0.653***	0.686***	0.708***	0.680***	0.704***	0.691***
	(35.09)	(57.11)	(50.99)	(45.06)	(45.72)	(35.16)	(35.09)
ncogall_std							
auc	0.451***						0.451***
	(51.88)						(51.88)
ncog_std7							
auc		0.466***					
		(65.47)					
ncog_std11							
auc			0.455***				
			(71.47)				
ncog_std16							
auc				0.415***			
				(34.35)			
ncog_std7_11							
auc					0.452***		
					(53.53)		
ncog_std11_16							
auc						0.422***	
						(32.67)	
N	32935	64120	57690	56555	46265	40675	32935

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NLSY – Measure Comparison (Age 8)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
var	model1	model2	model3	model4	model5	model6	model7	model8
piatmath8	0.05**	0.05**	0.05**					
	(0.00)	(0.00)	(0.00)					
piatrec8				0.04**	0.04**	0.04**		
				(0.00)	(0.00)	(0.00)		
nco_ext8		0.30**			0.30**			
		(0.04)			(0.04)			
nco_int8			0.20**			0.22**		
			(0.04)			(0.04)		
cog8							0.49**	0.41**
							(0.04)	(0.04)
nco8								0.32**
								(0.04)
female	0.33**	0.34**	0.32**	0.36**	0.38**	0.37**	0.42**	0.39**
	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)
white	0.33**	0.35**	0.32**	0.41**	0.43**	0.40**	0.39**	0.42**
	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
black	0.23**	0.25**	0.32**	0.29**	0.29**	0.36**	0.25**	0.27**
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)
_cons	7.70**	7.77**	7.70**	7.78**	7.91**	7.83**	9.06**	9.05**
	(0.14)	(0.15)	(0.15)	(0.14)	(0.15)	(0.15)	(0.10)	(0.10)
N	4,716	3,958	3,958	4,698	3,939	3,939	4,411	4,093
r2_a	0.05	0.07	0.06	0.04	0.06	0.05	0.05	0.06

A */** next to the coefficient indicates significance at the 10/5% level.

General Framework

$$Y_{i,t'} = \beta_t X_i + \gamma_t \theta^{c}_{i,t} + \gamma_t \theta^{nc}_{i,t} + \varepsilon_t \quad (4)$$

Childhood at 7, 11, 16 and adult life from 23 to 60.

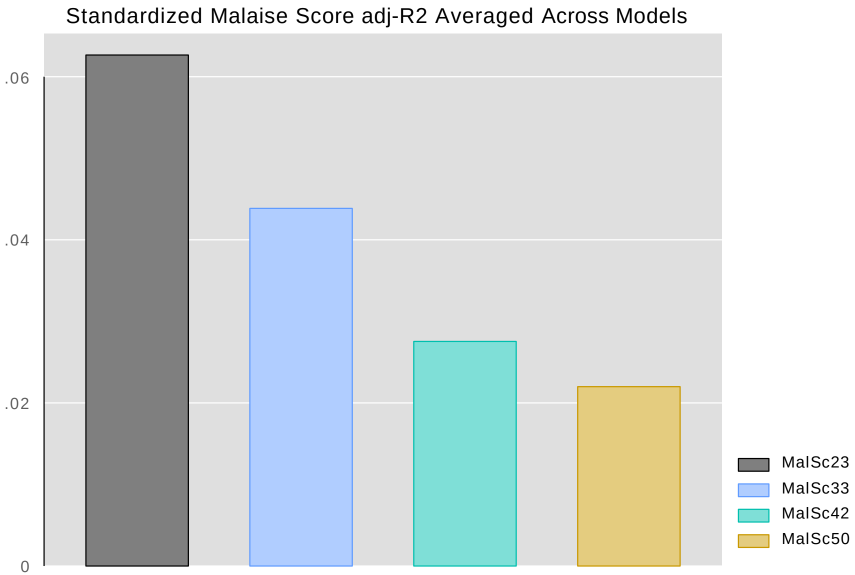
Cognitive and noncognitive skills during childhood are used to predict adult outcomes

Test different age and skill combination of childhood predictors:

7, 11, 16, 7-11, 11-16, 7-11-16

cog. only, noncog. only, both – at each of the age combinations above

Use minimal set of other covariates: gender and ethnicity


Standardized Malaise Score adj-R2 Averaged Across Models
.06
.04
.02
0
MalSc23
MalSc33
MalSc42
MalSc50

adj R2 values for Log Weekly Earnings - average over all specifications.

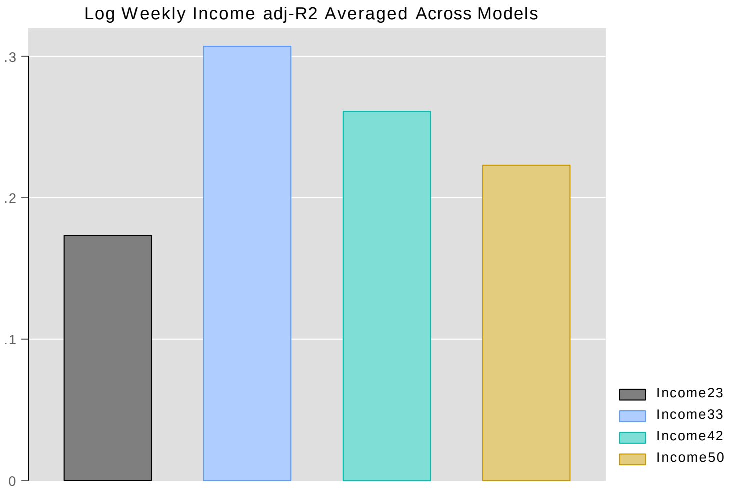


Figure: Log weekly income at age 33, predicted by child skills at different ages

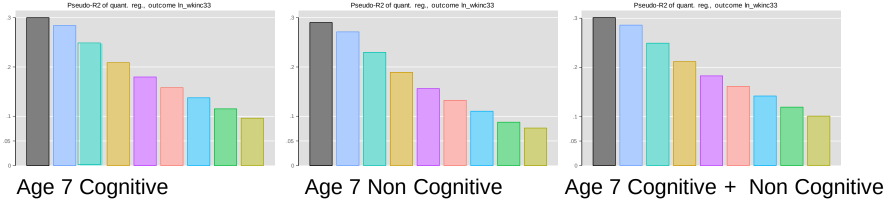
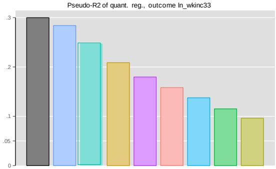
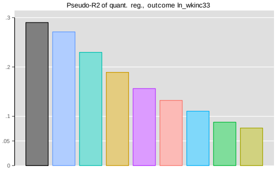


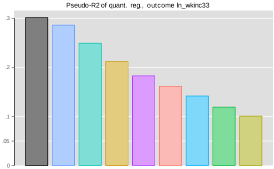
Figure: Log weekly income at age 33, predicted by child skills at different ages



Age 7 Cognitive

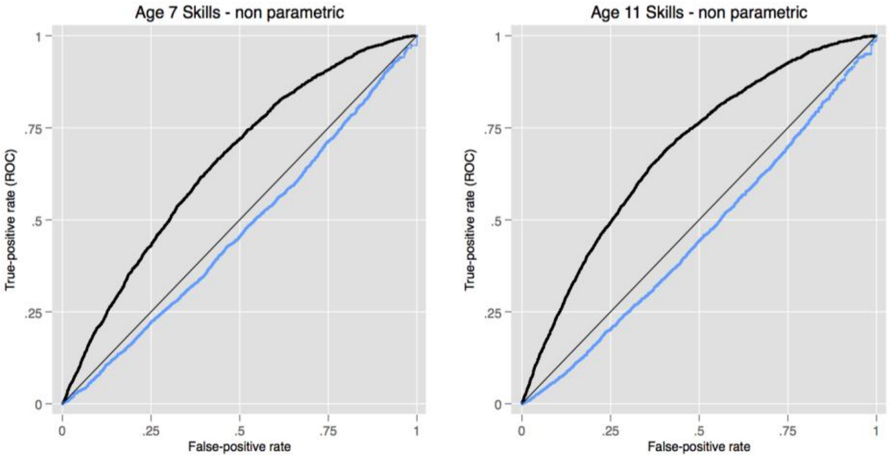


Age 7 Non Cognitive



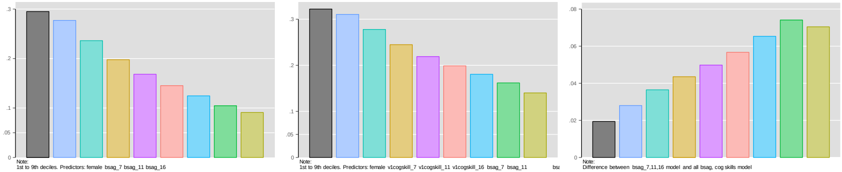
Age 7 Cognitive + Non Cognitive

Pred. validity of skills for Q5 of Log Earnings



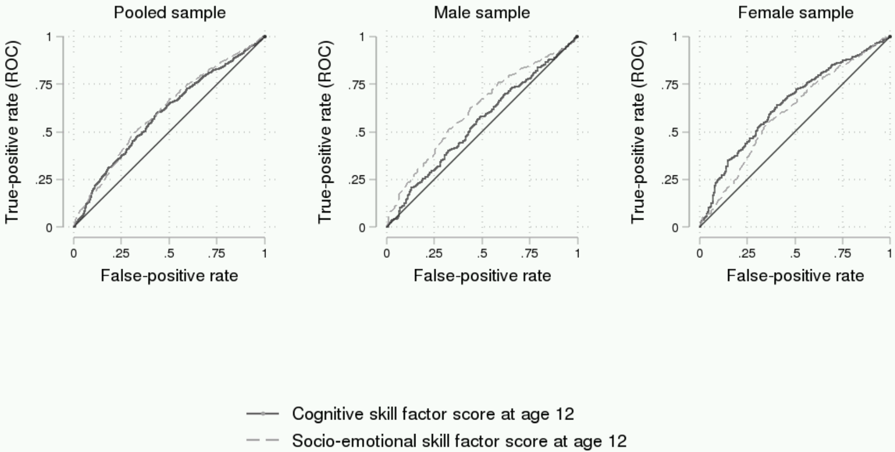
Consistent with prior literature, income at higher deciles are harder to predict with early childhood skills, suggesting greater volatility. Overall there aren't huge differences among skill measurements at different ages. Measures taken at later age provide slightly better fit. This improvement is greater at higher deciles than at lower deciles, although the magnitude of improvement remains small.

Figure: Log weekly income at age 33, predicted by cognitive and noncognitive skills



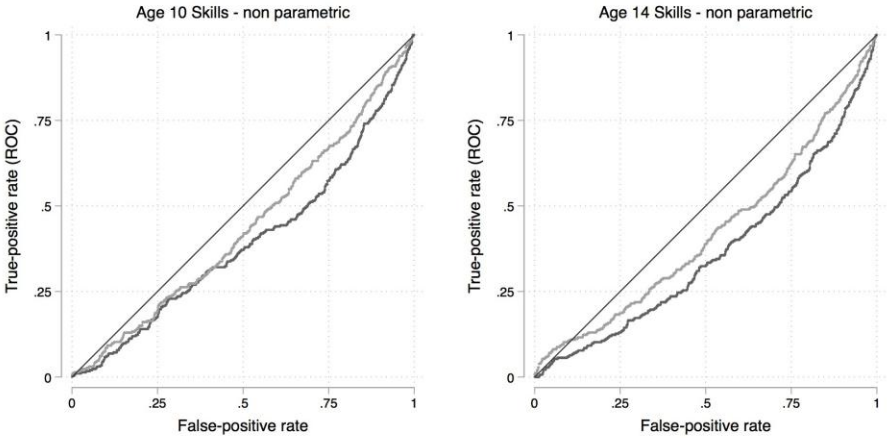
Cognitive skills contribute more to predicting income at higher deciles. Note that the right-most figure has different scale from the other two.

Pred. validity of skills for self-rated health for ages 26-30

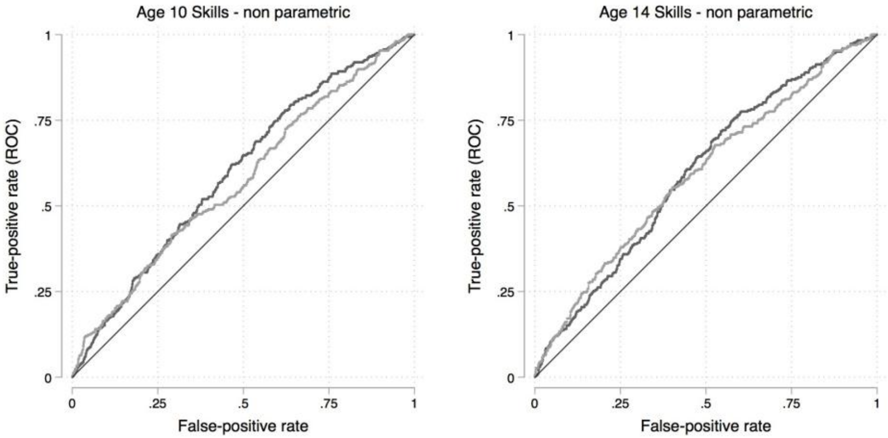


Note: Cognitive vs. noncognitive skills at age 12.

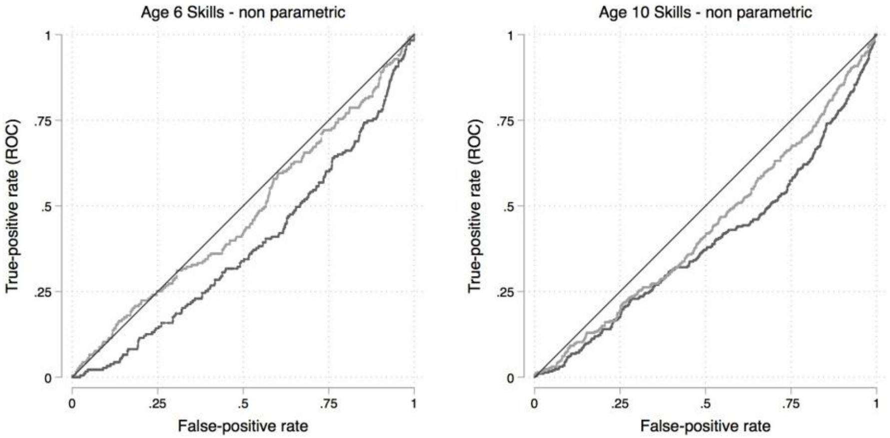
Pred. validity of skills for Q1 of childwage30



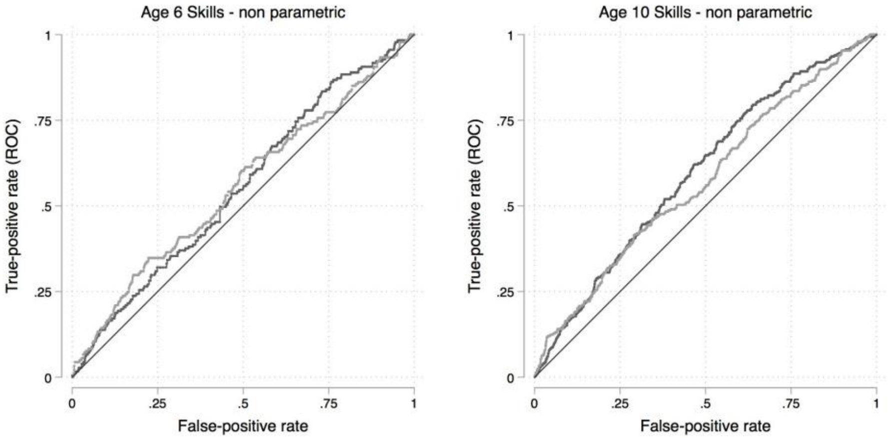
Pred. validity of skills for Q5 of childwage30



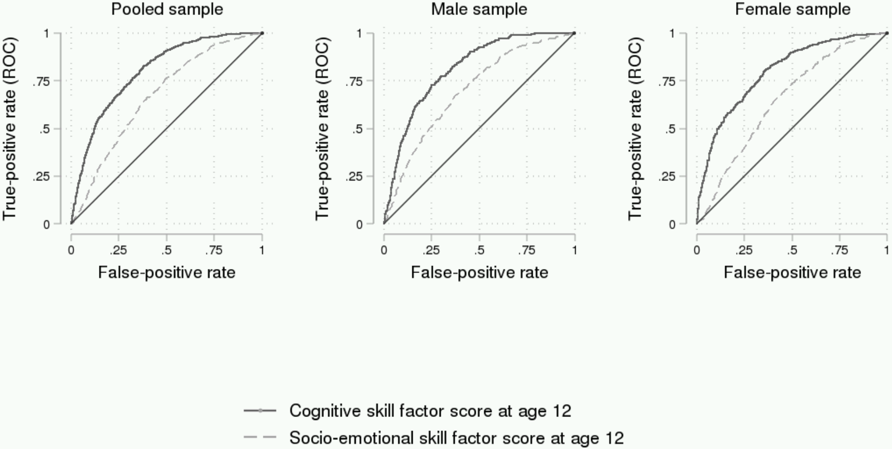
Pred. validity of skills for Q1 of childwage30



Pred. validity of skills for Q5 of childwage30



Pred. validity of skills for college graduation by age 26

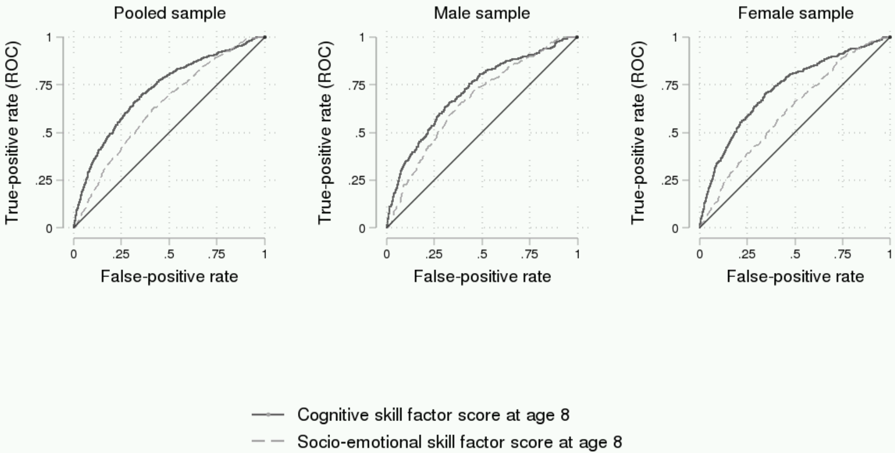


Note: Cognitive vs. noncognitive skills at age 12.

Pred. validity of skills for college graduation by age 26

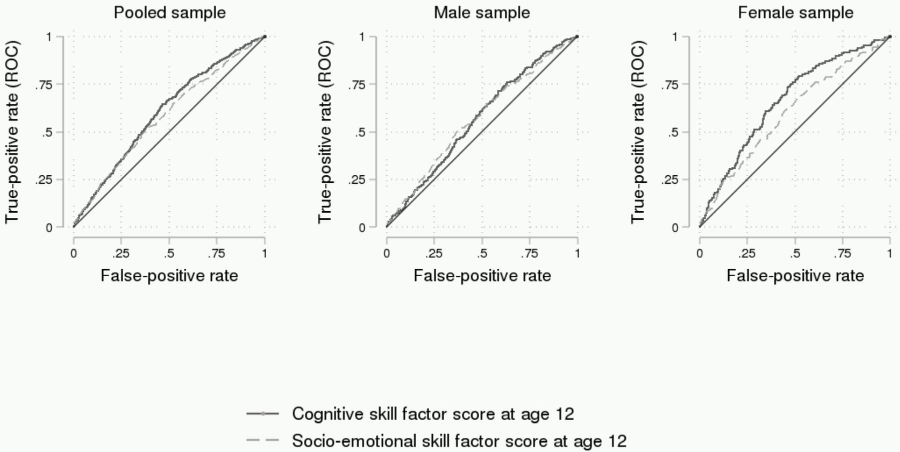
Note: Cognitive vs. noncognitive skills at age 4.

Pred. validity of skills for college graduation by age 26



Note: Cognitive vs. noncognitive skills at age 8.

Pred. validity of skills for age 24-30 wage income in top decile



Note: Cognitive vs. noncognitive skills at age 12.

Unobserved heterogeneity

Liu, Moon and Schorfheide (2015) estimates the following random coefficient model

$$y_{it} = \lambda_i w_{it-1} + \rho y_{it-1} + \gamma z_{i,t-1} + E_{it}, \lambda_i \sim F, E_{it} \sim G \tag{5}$$

where λ_i is individual-specific unobserved heterogeneity and w_{it} is independent of y (such as constant, time trend or exogenous variation).

λ_i is estimated using Tweedie correction, a convenient empirical Bayes method when the distribution of λ_i is assumed to be Gaussian.

The goal is to construct a forecasting model that produces the best projection, which are provided as .

$Y^*_{it} = \lambda_{i,\ t-1} + w_{t-1} + \gamma z_{i,t-1} + \rho y$

Unobserved heterogeneity in forecasting life outcomes

We consider two forms of unobserved heterogeneity:

- Heterogeneity of individual skill dynamics
- Heterogeneity of income dynamics

Within the NCDS data, we find no role for either type of heterogeneity.

We consider that the role of unobserved heterogeneity may be minimal due the relationship between prior skill and current skill (as well as prior outcome and current outcome) may be homogenous and relatively stable within the population, but consider that there may instead be unobserved heterogeneity in the relationship between skills and outcomes.

We can test for this using a two stage method of forecasting that first uses childhood skill to predict adult skill, and then regresses the outcome of interest on the estimated value of adult skill.

Next Steps

- Recently began duplicate analysis using GSEOP data
- Exploring additional nationally representative longitudinal data sets for cross-national comparison
- Improve analysis of health outcomes.
- Out of sample validation using data from policy interventions (Perry Preschool, Abcedarian Prooject)