The Effect of Early Cognitive Ability on Earnings Over the Life-Cycle

Torberg Falch — Sofia Sandgren Massih

Abstract. This paper utilizes information on cognitive ability at age 10 and earnings information from age 20 to 65 to estimate the return to ability over the life-cycle. Cognitive ability measured at an early age is not influenced by the individual's choices of schooling. We find that most of the unconditional return to early cognitive ability goes through educational choice. The conditional return is increasing for low levels of experience and non-increasing for experience above about 15–25 years. The return is similar for men and women, and highest for individuals with academic education. Only a small part of the return can be explained by higher probability of having a supervisory position.

1. Introduction

Information on the productivity of individuals entering the labor market is limited. Novice workers have no work history to prove their competence and abilities. Over time, employers can learn more about individual workers ('employer learning') as argued by Farber and Gibbons (1996) and Altonji and Pierret (2001), and workers may learn more about their own productivity ('employee learning') and change their wage claims and career plans accordingly. Therefore, hard-to-observe characteristics relevant to productivity will be increasingly rewarded as they are revealed by the market when workers gain experience.

Empirical research is limited because few variables that are hard to observe for the actors in the labor market are observable by researchers. The existing evidence is mainly based on the US Armed Forces Qualifying Test (AFQT) in the National Longitudinal Survey of Youth 1979 (NLSY79). Farber and Gibbons (1996) and Altonji and Pierret (2001) argue that AFQT is correlated with productivity but not observed by the market. The present paper adds to the literature by exploiting a completely different data-set to estimate the relationship between experience and the return to cognitive ability.

Our data differ from NLSY79 in many ways. The data consist of all individuals in the third grade (10 years of age) in 1938 in the city of Malmö, Sweden, with earnings information up to the age of 65. As hard-to-observe variables in the labor market, we use several cognitive ability measures from the third grade, including an IQ test, teacher grading, and teacher subjective evaluations. NLSY79 consists of individuals aged 15–22 when they conducted the AFQT test.

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One weakness of our data is that it includes only one cohort. This makes it challenging to distinguish between experience, education, age, and time effects. In order to focus on the interaction between cognitive ability and experience, our baseline approach is to condition out education, age, and time effects from the model, and to allow for a flexible effect of experience. It turns out that the results are not sensitive to the model specification. The estimated dynamic return to cognitive ability conditional on education is similar in the baseline model, the parsimonious models, and the models with individual fixed effects.

The paper is organized as follows. In the next section we lay out the empirical approach. The data are presented in Section 3, and Section 4 presents the empirical results. We estimate how the effect of a compound measure of cognitive ability in third grade depends on experience using both semi-parametric and parametric specifications; we split the sample according to gender and education level, and we use different measures of early cognitive ability. Finally, we investigate whether early cognitive ability is related to the probability of holding a supervisory position. Section 5 concludes.

2. Empirical approach

Productivity is related to both observable and unobservable individual characteristics. Over time, the actors in the labor market learn about unobserved characteristics by observing actual productivity. Better estimates on characteristics that are not directly observable will change the return to observed characteristics that are correlated with the hard-to-observe variables under statistical discrimination.

Assume that the true logarithm of productivity f_{it} of worker i at time t is

$$f_{it} = \alpha Z_i + \beta S_i + h(x_{it}) + \varphi_t + \mu_{it}, \quad [1]$$

where Z_i is cognitive ability, S_i is schooling, x_{it} is experience, $h(x_{it})$ is the experience profile of productivity, and μ_{it} is an independent and identically distributed productivity shock. φ_t reflects that average productivity increases over time. x_{it} is uncorrelated with Z_i and S_i when the individual characteristics are time-invariant.

The expectation about Z may depend on S and improve as more noisy signals about true productivity arrive. Expected productivity can be written

$$E(f_{it}|S_i, x_i, \varphi_t) = a(x_{it}) + b(x_{it})S_i + h(x_{it}) + \varphi_t + \eta_{it}, \quad [2]$$

where $a_i(x_{it})$ represents the noisy estimate of αZ_i, and $b(x_{it})$ depends on the learning process. Because learning improves the knowledge of Z_i, and learning takes place as experience increases, the actors can rely less on variables that are correlated with Z for experienced workers than for novice workers.[1]

In this paper we are interested in how the effect on wages of early cognitive ability depends on experience. Thus, we estimate the model

$$w_{it} = A(x_{it})Z_i + B(x_{it})S_i + h(x_{it}) + \varphi_t + \varepsilon_{it}, \quad [3]$$

with various restrictions on $A(x_{it})$. With market learning on Z, $\partial A/\partial x \geq 0$ and market learning with statistical discrimination yields $\partial B/\partial x \leq 0$. The second derivatives depend on the noise in the productivity signals. This paper focuses on the estimate of $A(x_{it})$ as explained below.[2]

3. Data

We use the Malmö Longitudinal Data-set, possibly the longest longitudinal data-set existing.[3] The data include all children in third grade in Malmö municipality in 1938, originally 1,542 individuals. The data collected in 1938 includes information on family background as well as different cognitive ability measures. The earnings information comes from different registers collected about each fifth year from the age of 20 in 1948 until the age of 65 in 1993, which was the formal retirement age in Sweden.[4] A host of other information, such as education level and work experience, was collected in four different questionnaires distributed in 1964, 1971, 1984 and 1994. The response rates for the questionnaires have been high, around 75 per cent each time. The IQ test conducted at military enrollment is matched onto the sample for men.

The cognitive ability measures include an IQ test for all third-graders in the spring of 1938, the year the normal-aged pupils turn 10 years of age.[5] When the original information was collected in 1938, each child in third grade in any school within the municipality of Malmö was included. The IQ measure is available for the whole original cohort of third graders, with the exception of seven girls.[6] The test was constructed after thorough testing on third-graders the year before and consisted of four parts: word opposites, sentence completion, perception of identical figures, and disarranged sentences. In addition, there is information on grade point average and teacher ratings. The teachers were asked to make two types of ratings of the students in their class. In the first rating, they gave an objective measure of overall cognitive ability on a scale from one to five (Rating O). In the second rating, only relative cognitive ability within class was to be considered by identifying the 15 per cent weakest and strongest students (Rating W).

Mean values and correlation coefficients between the different measures of cognitive ability are presented in Table 1, separately for women and men. The mean IQ score is slightly below 100 for both for women and men, which Husèn (1950) explains by the fact that there were more over-aged than under-aged pupils in the cohort and the over-aged pupils had a propensity to perform below average. The correlation coefficients are in the range 0.45 to 0.75, with the lowest coefficients for rating within class.

To simplify the empirical analysis, we will rely mainly on one compound variable of cognitive ability. A principal component analysis on standardized values yields very similar weights for the four different ability measures. Thus, we simply calculate the mean of the individuals' standardized values of the ability measures and denote this variable 'Early cognitive ability'. Table 1 shows that the correlations with the original ability measures are in the range 0.79–0.91. For each individual, there is information from at least two of the original ability measures. Regarding the IQ test for men done at military enrollment at age 20, it is highly correlated with the early cognitive ability variables, indicating that the reliability of the variables is good.

We have register data on annual earnings from 13 different years.[7] For the first years, 1948, 1953, 1958 and 1963, only the tax registers in Malmö were searched for information on annual earnings, and data on earnings are missing for some of those who reported in the questionnaire in 1964 that they worked these years.[8] From 1971 and onward, we use earnings data collected by Statistics Sweden, and thus all individuals alive and with legal earnings in Sweden are included. For the years 1968 and 1971, we have earnings information from both the national tax register and Statistics Sweden, and the data are almost identical.[9] The earnings in the data seem reasonably representative for Sweden.[10] However, the general decline in the earnings dispersion in Sweden in the 1970s (see Edin and Holmlund, 1995; Hibbs and Locking, 1996) is hardly visible for this cohort.[11]

Table 1. The measures of cognitive ability: descriptive statistics

	Observations	Mean	Standard deviation	Correlation coefficients with				
				IQ 10	GPA	Rating O	Rating W	Ability
A. Men								
IQ in third grade (IQ 10)	834	97.7	16.02					
Grade point average third grade (GPA)	799	3.5	0.57	0.620				
Teacher overall rating (Rating O)	765	2.89	1.21	0.651	0.729			
Teacher rating within class (Rating W)	765	2.00	0.52	0.451	0.555	0.641		
Early cognitive ability (Ability)	834	0.00	0.99	0.805	0.871	0.899	0.785	
IQ at age 20	653	97.6	16.47	0.740	0.602	0.615	0.417	0.705
B. Women								
IQ in third grade (IQ 10)	701	98.5	16.78					
Grade point average third grade (GPA)	687	3.4	0.54	0.636				
Teacher overall rating (Rating O)	651	2.96	1.25	0.664	0.742			
Teacher rating within class (Rating W)	651	2.02	0.54	0.537	0.589	0.715		
Early cognitive ability (Ability)	708	0.00	1.01	0.829	0.859	0.909	0.832	

Notes: Calculated on the original sample in 1938. Early cognitive ability is an average of the other ability measures in the table. Rating O is teacher rating of overall cognitive ability on a scale from one to five and Rating W is teacher rating of relative cognitive ability within class on a scale from one to three.

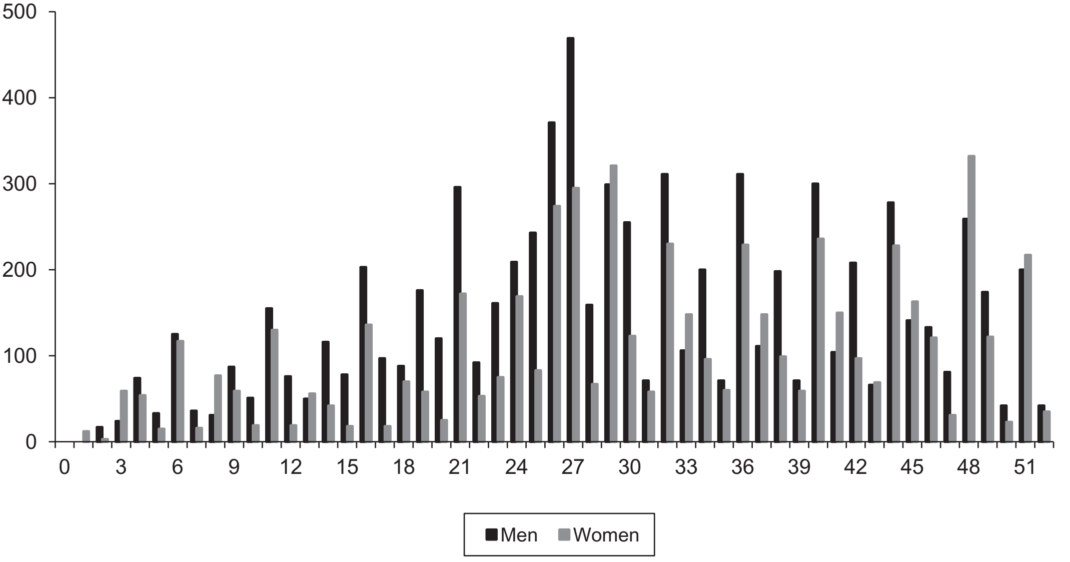
In the conditional model estimated below, the return to cognitive ability is related to experience. We will rely mainly on potential experience. Actual experience may include information to the employers about worker quality and effort because it is an outcome variable itself. In particular, one would expect grade repetition towards the end of compulsory schooling to convey information relevant for employers. When constructing potential experience, we take into account possible grade repetition up to grade three. Potential experience is calculated as year — 1935 — years of schooling. The normal-aged children enrolled in school in 1935. We will show that the results are not sensitive to replacing potential experience with actual experience. Actual experience is calculated using occupational information given in the questionnaires, which implies that there are some missing observations.[12]

Notice that, because we only have data for one cohort and no variation in years of education within individuals, potential experience and education are perfectly correlated in the cross-section. Thus, the effects of potential experience, education, and year dummies cannot be separately identified, and it follows that interaction effects between education and potential experience ($B(x_{it})$ in equation [3]) cannot be identified in models that include interactions effects between potential experience and dummy variables for year.

Educational information is collected from both the questionnaire in 1964 and school registers, and information is missing for only 3.5 per cent of the original sample. Figure 1 presents the number of observations for which there is information on earnings, education and potential experience. Because earnings data are only available each fifth year up to the age of 40, and certain types of education are more common than others, the number of observations varies.

Because school ends in the spring, the first half year of working is not included in the analysis. The lowest possible potential experience is therefore one. Individuals with 12 years of education have potential experience of one in 1948, the first year with earnings information. In fact, no men in the sample undertook 12 years of education.[13] Thus, in the sample of men, the lowest observed potential experience is 2 years. About 45 per cent of both men and women

Figure 1. The number of observations for each level of potential experience



finished school after 7 years of compulsory primary education, and they had 6 years of potential experience in 1948. The number of observations for each experience level increases for experience levels above about 20 years, because the earnings information was collected with smaller time intervals from 1968 and the scope of the data collection improved.[14]

Table 2 presents descriptive statistics for the variables used in the analysis. We classify education into four different types. For example, vocational school and lower secondary school involved a similar number of years in school, but with very different content. There are pronounced differences between the genders. Lower secondary education was most common among women, vocational education was most common among men, actual experience is lower for women, and women work part-time to a larger extent. The table includes information for both the original sample and the subsample of individuals for whom we have all necessary information to be included in the analysis. The difference between the samples is small for all variables. Formal tests on the differences in mean values across the samples are, however, significant at the 1 per cent level in five cases. For both women and men, the share that is retired in 1993 is significantly higher and the share with only primary education is significantly lower in the subsample. In addition, for women, early cognitive ability is lower in the subsample.

4. The return to cognitive ability over the life-cycle

We start out by focusing on the sample of men in Sections 4.1–4.4, and estimate similar models for women in Section 4.5. First we present unconditional returns to the variable 'Early cognitive ability' at different ages. Thereafter we estimate conditional models. We investigate whether the relationship between experience and the return to cognitive ability is sensitive to the handling of experience, education, part-time work, and individual characteristics, and also estimate models distinguishing between different cognitive ability measures.

4.1. Unconditional return to cognitive ability and education

Figure 2a presents the unconditional returns to one standard deviation in early cognitive ability for men by estimating separate models for each year. In 1948 and 1953, at ages 20 and 25, the return to standardized cognitive ability is about 6 per cent and significant at 5 per cent level. Thereafter, the unconditional return increases to about 25 per cent around 1970, and declines to below 20 per cent in the 1980s.

Some of the return to cognitive ability described in Figure 2a is likely to go through educational choices. High ability individuals are more likely than low ability individuals to undertake higher education. The correlation of early cognitive ability and years of education is slightly above 0.5.[15] Figure 2b presents the return to ability from a model formulation expanding the unconditional model with years of education allowing for year specific returns of both ability and education. The return to ability is lower in the conditional model, and increases to a smaller extent in the 1950s and 1960s.[16] A major effect of cognitive ability in economic terms seems to be on educational choices.

One hypothesis from Section 2 is that the return to education declines in experience in a model that include variables that are hard to observe in the market. This prediction relies, however, on the assumption that the true effect on productivity is constant. The Scandinavian evidence indicates that the return to education increases in the first years of the working career; see e.g. Hægeland *et al*. (1999) and Sandgren (2007). The experience profile is steeper

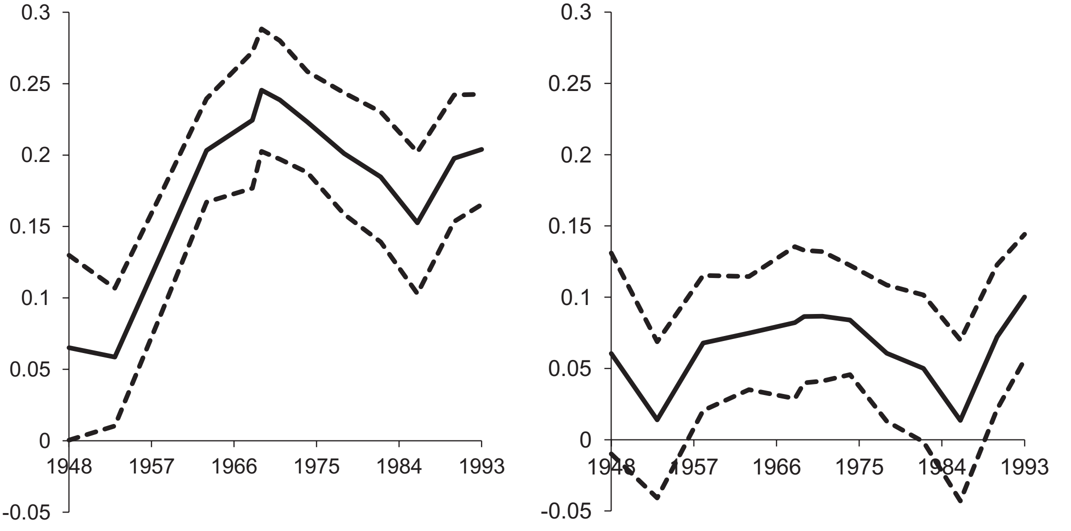
Table 2. Descriptive statistics for independent variables

	Men				Women			
	Individuals, original sample	**Original sample**	**Subsample**	**Test on difference**	**Individuals, original sample**	**Original sample**	**Subsample**	**Test on difference**
Early cognitive ability	834	0.001	–0.007	0.550	708	–0.001	–0.061	<0.001
		(0.99)	(0.99)			(1.01)	(1.01)	
Potential experience in years, 1993	755	49.1	49.1	0.027	618	49.3	49.3	0.013
		(2.50)	(2.50)			(2.04)	(2.05)	
Years of education	755	8.91	8.95	0.027	618	8.68	8.71	0.013
		(2.50)	(2.50)			(2.04)	(2.05)	
Primary school, 7 years of education	755	0.46	0.45	<0.001	618	0.48	0.47	0.007
Vocational school, about 9 years of education	755	0.27	0.28	0.012	618	0.25	0.25	0.178
Lower secondary school, about 9 years of education	755	0.13	0.13	0.135	618	0.18	0.18	0.420
Upper secondary school and above, at least 12 years of education	755	0.14	0.15	0.246	618	0.09	0.10	0.138
Marital status — have never been married	788	0.09	0.09	0.104	661	0.06	0.04	0.016
Retired, 1993	589	0.60	0.63	<0.001	548	0.55	0.56	<0.001
Actual experience in years, 1993	550	45.2	44.8	0.028	392	33.9	33.5	0.117
		(6.9)	(6.7)			(12.6)	(12.4)	

Notes: Mean values with standard deviations in parentheses. The test on the difference in mean values between the subsample and the original sample reports p-values. The subsamples include observations of individuals without missing information for earnings or for any of the reported variables (except retired and actual experience in 1993), which amounts to 726 men and 602 women.

Figure 2. The effect of early cognitive ability with 95 per cent confidence interval. Dependent variable is log yearly earnings for men

a) Unconditional effects b) Conditional on years of education



for highly educated workers than for workers with low education. Figure 3 presents the unconditional return to education, which increases up to the age of 40 in 1968, and decreases slightly thereafter. Figure 3 also presents the results from the model conditioning on early cognitive ability, the same model as in Figure 2b. The return to education is lower in the conditional model each year,[17] and there is a tendency of an increasing difference, as one would expect. The difference is about 0.5 percentage points up to 1953, about 1.2 percentage points in 1958–70, and about 1.5 percentage points thereafter.

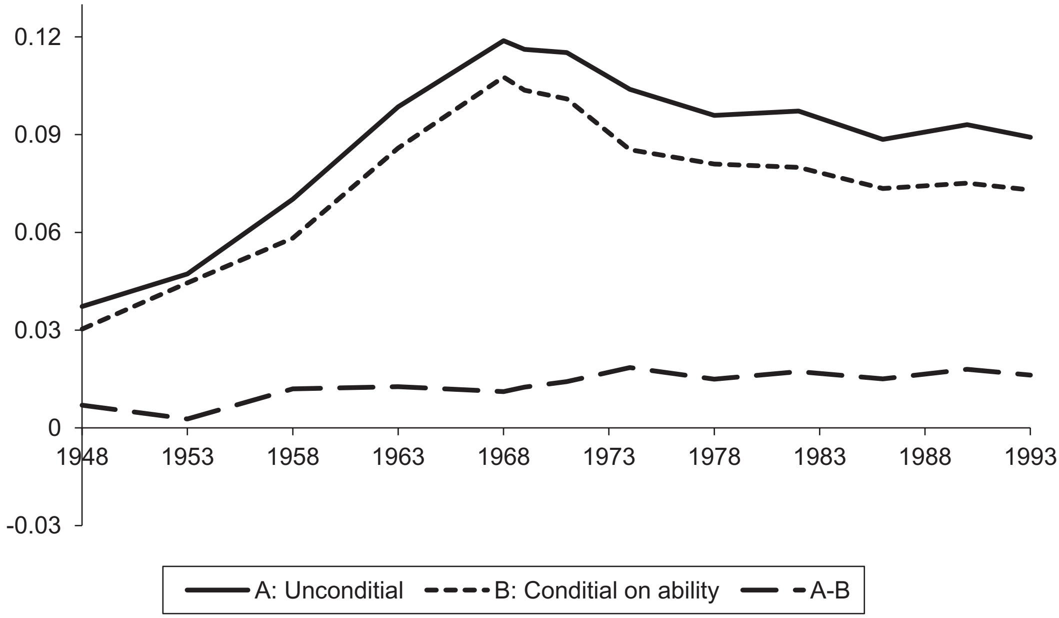
4.2. Conditional return to cognitive ability

We start out by investigating the functional form of the interaction effect between early cognitive ability and potential experience by a semi-parametric approach. We construct dummy variables for potential experience with 2-year intervals (1 and 2 years of potential experience, 3 and 4 years, and so on) and interact them with the variable 'Early cognitive ability'. Except for the dummy variables for potential experience, we use the same model specification as the models in Table 3 below that parameterize the interaction.

Figure 4 presents the coefficients of the interaction terms with 95 per cent confidence intervals (in addition to two parametric models presented below). The return to one standard deviation in early cognitive ability is estimated to below 3 per cent in six out of seven estimates for potential experience below 15 years. In contrast, for 15–36 years of potential experience, all 11 estimates are above 3 per cent, and four of the estimates are above 5 per cent. Thus, it seems that the return to cognitive ability increases after the first years of the working career. The return seems to be somewhat lower when potential experience exceeds 36 years.

Table 3 presents different models parameterizing the interaction between experience and cognitive ability. Because our focus is on the interaction between ability and potential

Figure 3. The return to education, unconditional and conditional on early cognitive ability



experience, we condition on a range of other interactions with potential experience. Interaction with time-specific effects might be important because wage distribution is not constant over time. Thus, years of education is collinear in the model because the data include only one cohort, but, more importantly, the model fully captures the interaction $B(x_{it})S_i$ in equation [3] above. In addition to the third polynomial of potential experience, the model includes dummy variables for three educational types, for never being married, for working part-time, and for having retiree. All variables are interacted with potential experience. We show below that the main results are not sensitive to either a more or a less flexible specification of experience. In addition, the results are robust to the exclusion of the other control variables, as well as to the inclusion of individual fixed effects.

We start with a model linear in ability in column (1) in Table 3. On average over the life-cycle, the conditional return to one standard deviation in the variable ‘Early cognitive ability’ is slightly above 4 per cent and highly significant.[18] The estimate is below the results of Altonji and Pierret (2001) and Schönberg (2007), which are based on tests taken later in life and thus partly capture elements of non-compulsory educational choices. In column (2) we add a linear interaction with potential experience, a model formulation similar to Altonji and Pierret (2001). The interaction term is positive, but clearly insignificant. If employer learning is strongest early in an employee’s working life, a linear interaction will not yield a good description of the life-cycle return to ability. In column (3) we follow Schönberg (2007) and include interaction with experience squared. As in Schönberg, we find that, without any experience, the return to ability is close to zero, but we find smaller coefficients for the interaction terms. The return to ability is maximized at about 35 years of potential experience, clearly higher than the result of about 20 years in Schönberg.[19]

Multicollinearity seems to limit the possibility of estimating precise coefficients in models with flexible functional forms. None of the three terms that include early cognitive ability in

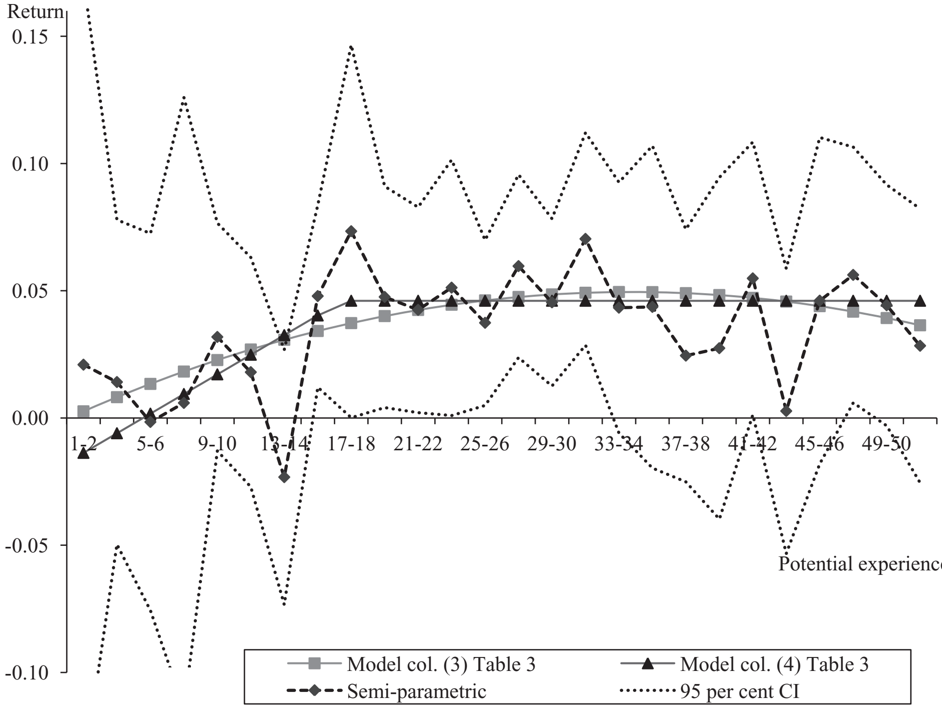
Table 3. The effect of cognitive ability over the life-cycle. Dependent variable is log yearly earnings for men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Early cognitive ability	0.042**	0.029~	–0.002	–0.022	–0.020	0.047**	0.007	–0.039
	(0.011)	(0.016)	(0.025)	(0.029)	(0.029)	(0.012)	(0.025)	(0.028)
Interaction between ‘Early cognitive ability’ and								
Potential experience/100	—	0.044	0.300	—	—	—	0.246	—
		(0.054)	(0.185)				(0.186)	
Potential experience squared/100	—	—	–0.0044	—	—	—	–0.0033	—
			(0.0029)				(0.0030)	
Potential experience/100. Linear to 17, constant thereafter	—	—	—	0.416*	0.386~	—	—	0.535**
				(0.204)	(0.199)			(0.194)
Potential experience/100. Constant to 17, linear thereafter	—	—	—	–0.019	—	—	—	—
				(0.064)				
Interaction between potential experience and Education	—	—	—	—	—	–0.0082*	–0.0083*	–0.0083*
						(0.0033)	(0.0033)	(0.0033)
Year	Yes	Yes	Yes	Yes	Yes	No	No	No
Dummy variables for education type	Yes	Yes	Yes	Yes	Yes	No	No	No
Test for joint significance of ‘Early cognitive ability’ at level and interactions, p-value	<0.001	0.001	0.003	0.002	0.001	<0.001	0.001	<0.001
R^2	0.5574	0.5575	0.5576	0.5576	0.5576	0.5529	0.5531	0.5534

Notes: 7,669 observations. In addition to the reported variables, the models include: a cubic of potential experience, marital status, year specific effects, an imputed dummy variable for part-time work, a dummy for early retirement, and three dummy variables for education type [only columns (1)–(5)]. All variables are interacted with potential experience. In columns (1)–(5), the education main effects are absorbed by the experience and year dummy variables. To calculate a meaningful R^2, the mean log wage is set equal to zero each year.

~, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

Figure 4. The effect of early cognitive ability over the life-cycle, semi-parametric and parametric models. Dependent variable is log yearly earnings for men



Note: The semi-parametric model includes dummy variables for experience as indicated, in addition to the control variables in the models in Table 3.

the model in column (3) are statistically significant at the 10 per cent level, but a test of joint significance cannot be rejected at 1 per cent level. Because the main effect of ability is negative, although very close to zero, the effect of ability is significant at the 1 per cent level only for potential experience above 12 years.[20]

Columns (4) and (5) in Table 3 present results from piece-wise linear regressions. We have investigated several different model formulations, but, with more than one knot, the estimates are imprecise. For models with one knot, the mean root square is minimized for the knot at 17 years of potential experience. This model is reported in column (4) in Table 3 and indicates that the return to ability is close to zero without any experience, increasing by 0.004 log points per year up to experience level of 17, and close to constant thereafter. The interaction term for experience up to 17 years is significant at 5 per cent level, and the effect of ability is significant at 1 per cent level for experience above 12 years. The model formulation in column (5) restricts the effect of ability to be constant for experience above 17 years.

Two different specifications in Table 3 seem to capture the main features of the data in a reasonably simple way; columns (3) and (5). In both models, the effect of cognitive ability is close to zero at the time of finishing education. The models are illustrated in Figure 4 above. They are very similar and impossible to distinguish statistically.

The models presented so far do not include education directly because education and potential experience are perfectly correlated each year and the models include interaction terms between year dummies and potential experience.[21] The interaction between education and experience can be identified, however, by excluding the interaction between year and potential experience from the model. That is done in the three last models in Table 3, which also exclude the three dummy variables for education type. The main effect of education is fully captured by the main effect of potential experience. The model re-specification hardly changes the effect of cognitive ability, and the interaction between education and experience is negative as predicted by the theory. Further, the education interaction effect is not sensitive to the handling of ability. The latter result indicates that the schooling and ability coefficients are not driven by the same learning process over the life-cycle. In the following, we use the initial flexible model formulation without identification of education effects.

4.3. The handling of experience and other individual characteristics

If employer learning is important, the return to education should be expected to depend on actual experience and not potential experience. We have estimated models in which potential experience is replaced with actual experience. The results are very similar to the models above, which is reasonable because the correlation coefficient between the experience variables is very high for men.[22]

The results are also fairly robust with regard to model specification of potential experience. In models where potential experience is replaced by dummy variables for years of education, the average return to ability increases slightly to 4.5 per cent, but the return to ability over the life-cycle is similar to the models reported in Table 3. The same is true for a parsimonious model without any interaction effects, except between potential experience and ability.

Because it is reasonable that little learning takes place late in the working career, we present results for the subsample of experience below 40 years in the first model in Table 4. The results are very similar to the previous models. For the quadratic specification, the curvature becomes slightly stronger, the interaction terms are significant at 10 per cent level, and the return to ability is maximized at about 25 years of potential experience.

The other models in Table 4 investigate the robustness of the results with regard to some other variables. Column (2) shows that the results are not sensitive to whether the dummy variables for marital status and retirement are included in the model. However, column (3) shows that the average return to cognitive ability increases when the dummy variable for working part-time is excluded. When considering working time to be a choice variable, the average return to cognitive ability increases to 6.2 per cent. The results in the second and third regressions in column (3) indicate that the estimated return to ability over the life-cycle is also sensitive to whether working part-time is included in the model. A closer look at the data reveals that, when the variable for working part-time is excluded, the return to ability above 44 years of experience increases markedly. If observations with potential experience above 44 years are excluded from the sample, both interaction terms in the second regression in column (3) in Table 4 are significant at 10 per cent level, and the coefficients are about twice as large as in the model including the dummy variable for part-time work. In column (4), we exclude observations for individuals who work part-time. For this reduced sample, the estimated return to ability over the life-cycle is close to the baseline models in Table 3.

Finally, there may be additional differences between individuals that we do not include in the models. In particular, when estimating the effect of early cognitive ability, one would like to keep constant other aspects of the early childhood of the individuals, such as family background and living conditions. The last column in Table 4 estimates fixed effect models. Notice that this model is over-parameterized in the sense that average characteristics over the

Table 4. The specification of individual characteristics. Dependent variable is log yearly earnings for men

Specification change compared with Table 3	(1) Only experience up to 40 years	(2) Excluding dummy variables for marital status and retirement	(3) Excluding the dummy variable for part-time work	(4) Excluding observations of part-time work	(5) Individual fixed effects
Early cognitive ability	0.040**	0.043**	0.062**	0.050**	—
	(0.011)	(0.012)	(0.015)	(0.011)	
R^2	0.5843	0.5477	0.2600	0.3728	—
Early cognitive ability	–0.020	–0.007	0.055~	0.007	—
	(0.030)	(0.025)	(0.033)	(0.026)	
Interaction between 'Early cognitive ability' and					
Potential experience/100	0.551~	0.363~	0.047	0.217	0.301
	(0.289)	(0.186)	(0.250)	(0.190)	(0.201)
Potential experience squared/100	–0.0109~	–0.0056~	–0.0007	–0.0022	–0.0047
	(0.0063)	(0.0029)	(0.0039)	(0.0030)	(0.0031)
Test for joint significance, p-value	0.001	0.002	<0.001	<0.001	0.316
R^2	0.5846	0.5479	0.2600	0.3732	0.7675
Early cognitive ability	–0.007	–0.018	0.029	–0.020	—
	(0.028)	(0.0029)	(0.039)	(0.031)	
Interaction between 'Early cognitive ability' and potential experience up to 17/100 (spline)	0.304	0.383~	0.206	0.431*	0.384~
	(0.192)	(0.199)	(0.265)	(0.209)	(0.227)
Test for joint significance, p-value	0.001	0.001	<0.001	<0.001	0.091
R^2	0.5845	0.5479	0.2601	0.3732	0.7675
Observations	5,941	7,669	7,669	7,258	7,669

Notes: Same model specification as in Table 3 columns (1), (3) and (4), except as indicated. The education main effects are absorbed by the experience and year dummy variables.
~, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

working life of the individuals, not only characteristics of the childhood, are also differenced out of the model. Thus, it is not possible to estimate the average return to cognitive ability in this case. But varying return to ability can be identified, and, in both the quadratic interaction specification and the spline specification, the return to ability over the life-cycle is almost identical to the estimates in the comparable models without fixed effects.

4.4. Heterogeneity across education and cognitive ability measures

Hard-to-observe cognitive ability is likely to be of different importance in different types of jobs. In the first part of this section, we focus on differences between educational types. In the second part, we estimate models using the individual measures of cognitive ability instead of the compound measure. We also present results using our measure corresponding to the US AFQT test to facilitate comparison with the US studies.

Table 5 presents results for two educational groups. We distinguish between those who have no more than vocational education, including primary education, and others who have at least lower secondary school.[23] There are clear differences in the average return to ability between

Table 5. Vocationally and academically educated. The dependent variable is log yearly earnings for men

	(1)	(2)	(3)
A. Vocational education			
Early cognitive ability	0.030*	–0.011	–0.020
	(0.012)	(0.026)	(0.032)
Interaction between 'Early cognitive ability' and			
Potential experience/100	—	0.222	—
		(0.192)	
Potential experience squared/100	—	–0.0026	—
		(0.0030)	
Potential experience/100. Linear to 17, constant thereafter	—	—	0.309
			(0.224)
Test for joint significance, p-value	0.011	0.086	0.036
R^2	0.5203	0.5206	0.5205
Observations	5,602	5,602	5,602
B. Academic education			
Early cognitive ability	0.069*	–0.004	0.015
	(0.029)	(0.054)	(0.062)
Interaction between 'Early cognitive ability' and			
Potential experience/100	—	0.695	—
		(0.464)	
Potential experience squared/100	—	–0.0133	—
		(0.0082)	
Potential experience/100. Linear to 17, constant thereafter	—	—	0.340
			(0.456)
Test for joint significance, p-value	0.017	0.026	0.046
R^2	0.4658	0.4665	0.4660
Observations	2,067	2,067	2,067

Notes: Same model specification as in Table 3 columns (1), (3) and (4), except as indicated. The education main effects are absorbed by the experience and year dummy variables.
˜, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

Table 6. The returns to the individual ability measures. The dependent variable is log yearly earnings for men

Measure of cognitive ability	**(1) Teacher rating within class**	**(2) Teacher overall rating**	**(3) GPA third grade**	**(4) IQ third grade**	**(5) IQ at age 20**
Cognitive ability	0.019~	0.031**	0.032**	0.049**	0.074**
	(0.010)	(0.011)	(0.011)	(0.011)	(0.013)
R^2	0.5610	0.5621	0.5541	0.5586	0.5291
Cognitive ability	–0.001	–0.008	0.012	0.017	0.005
	(0.025)	(0.027)	(0.021)	(0.027)	(0.032)
Interaction between cognitive ability and					
Potential experience/100	0.200	0.228	0.157	0.136	0.405~
	(0.187)	(0.192)	(0.167)	(0.200)	(0.209)
Potential experience squared/100	–0.0038	–0.0029	–0.0026	–0.0009	–0.0051
	(0.0030)	(0.0030)	(0.0027)	(0.0031)	(0.0033)
Test for joint significance, p-value	0.146	0.050	0.022	<0.001	<0.001
R^2	0.5611	0.5623	0.5541	0.5588	0.5296
Cognitive ability	–0.017	–0.026	0.009	–0.003	–0.025
	(0.030)	(0.032)	(0.025)	(0.032)	(0.036)
Interaction between cognitive ability and potential experience up to 17/100 (spline)	0.225	0.352~	0.143	0.321	0.621**
	(0.200)	(0.209)	(0.182)	(0.216)	(0.225)
Test for joint significance, p-value	0.136	0.016	0.013	<0.001	<0.001
R^2	0.5610	0.5624	0.5541	0.5588	0.5297
Observations	7,055	7,055	7,509	7,669	6,422

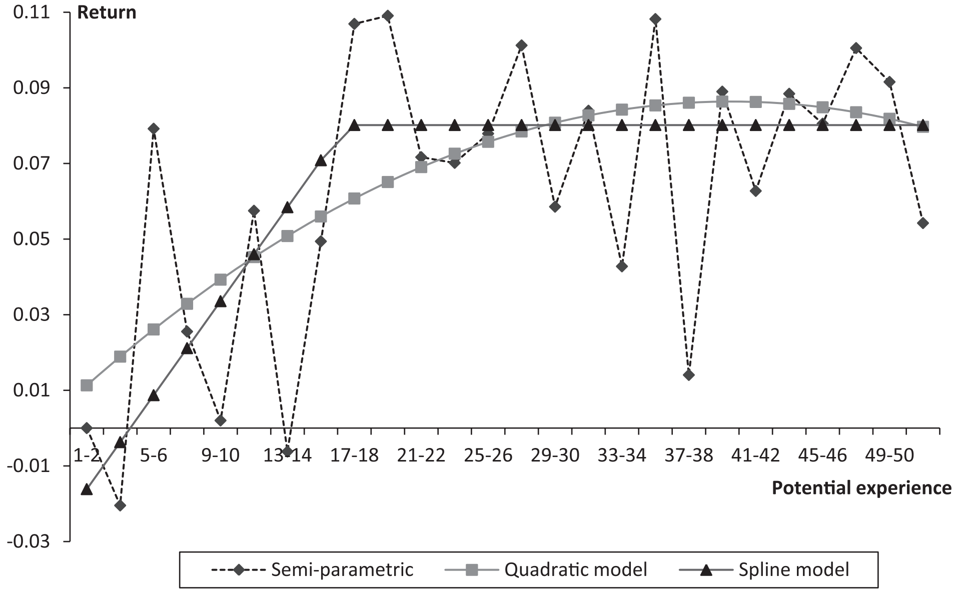
Notes: Same model specification as in Table 3 columns (1), (3) and (4), except as indicated. The education main effects are absorbed by the experience and year dummy variables.
~, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

the two groups. The conditional average return to ability is more than twice as large for individuals with academic education than for those with vocational education. In addition, it seems that the vocationally educated need more time in the labor market until the return to cognitive ability is maximized. According to the model specification in column (2), the return to ability is maximized at potential experience of 43 and 26 for individuals with vocational and academic education, respectively. Even though the estimates are imprecise, we do not find a strikingly different degree of learning across these educational groups, in contrast to Arcidiacono *et al*. (2010).

Our measure of cognitive ability is a compound variable based on four different cognitive ability measures in third grade. It is interesting to investigate the effect of the different measures of ability separately. Is it the IQ score that is important, or relative performance in class? In Table 6, we present models using only one of the cognitive ability measures at a time.

The return to teacher rating within class is smaller than teacher overall rating because of lower returns late in life. The return to grade point average in third grade is on average slightly

Figure 5. The effect of IQ at age 20 over the life-cycle, semi-parametric and parametric models. Dependent variable is log yearly earnings for men



Note: The semi-parametric model includes dummy variables for experience as indicated in addition to the control variables in the models in Table 3.

smaller than the return to our compound variable, and shows smaller changes over the life-cycle. Out of the individual cognitive ability measures in third grade, the return is highest for the IQ score. However, the return to IQ seems to increase late in life, which implies that the model specification with interaction between ability and squared experience is not the best characterization of the data.[24]

Lastly, column (5) in Table 6 presents the results when using the IQ score at military enrollment as the measure of cognitive ability. The effect of the IQ measured at age 20 is clearly higher than ability measured 10 years earlier. The average effect is larger than reported by Schönberg (2007) but smaller than reported by Altonji and Pierret (2001). While Schönberg includes only white men in the sample, Altonji and Pierret additionally include blacks and women. Thus, the results in Schönberg (2007) seem to be more comparable with the present study than with Altonji and Pierret (2001). Figure 5 presents results from a semi-parametric model together with the two parametric models in Table 6. This figure has the same pattern as Figure 4. Thus, the returns over the life-cycle to cognitive ability measured at age 10 and IQ at age 20 are very similar, except that the latter return is about 75 per cent higher at all ages.

Educational choices are likely to contribute to higher conditional return to IQ measured at age 20 than at age 10. Falch and Massih (2011) find that education has a major effect on IQ at age 20 in the present data,[25] which implies that return to IQ at age 20 in part captures the return to education. In unconditional models, we find that the average returns to IQ at age 10 and 20 are 0.19 and 0.20, respectively, the same as the return to our compound ability measure. This suggests that the difference in the estimated returns to cognitive abilities at ages 10 and 20 is related to educational choices.

4.5. Return to cognitive ability for women

For the cohort in our sample, women had less education, were home with children longer, and were housewives to a larger degree than is common today. Figure 6 presents the unconditional return to cognitive ability for women. Figure 6a shows that the return to cognitive ability is about 15 per cent each year, but varies somewhat early in the empirical period. The return over the life-cycle differs markedly from the case of men reported in Figure 2a, and it is hard to interpret the results as being in accordance with the hypothesis of market learning. The difference between men and women may be a result of the fact that the figures are conditional on labor market participation or that the decision to work part time differs across the genders. We can investigate the latter hypothesis. Up to potential experience of about 30 years, which is to the early 1970s, the share of women classified as having part-time work is about 40 per cent; this share declines to about 20 per cent thereafter. In Figure 6b, observations with part-time work are excluded. Thus, the picture is similar to that for men, although the return is lower.

Figure 7 and Table 7 present the results for the conditional models. Figure 7 shows that, compared with men, the return to cognitive ability is low for both high and low potential experience levels. However, the average conditional return estimated in column (1) in Table 7 is slightly higher for women than for men. It follows from Figure 7 that both the functional forms that interact ability with squared potential experience and the piece-wise linear experience give a reasonable fit to the data. All interaction terms in columns (3) and (4) in Table 7 are highly significant.[26] However, the negative return to ability for very low levels of potential experience is surprising. This result might be related to part-time work. Average ability is about 0.3 standard deviations lower for women working part-time than for women working full time. The models in the last two columns in Table 7 include only observations of working full time. In these models the main effect of ability is close to zero and clearly insignificant, as for men.

Figure 6. Unconditional return to early cognitive ability with the 95 per cent confidence interval. Dependent variable is log yearly earnings for women

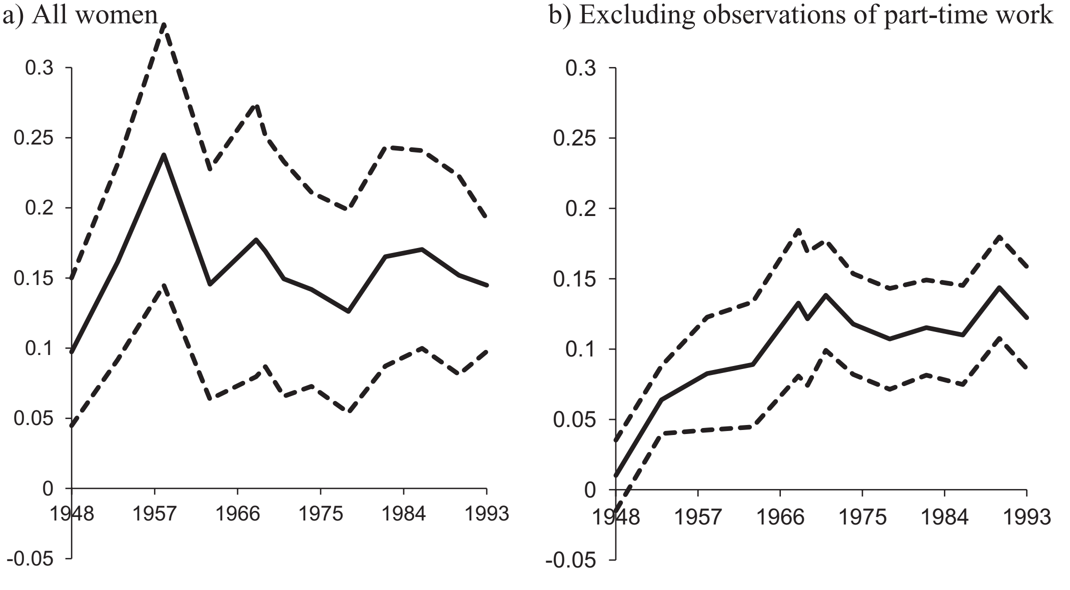
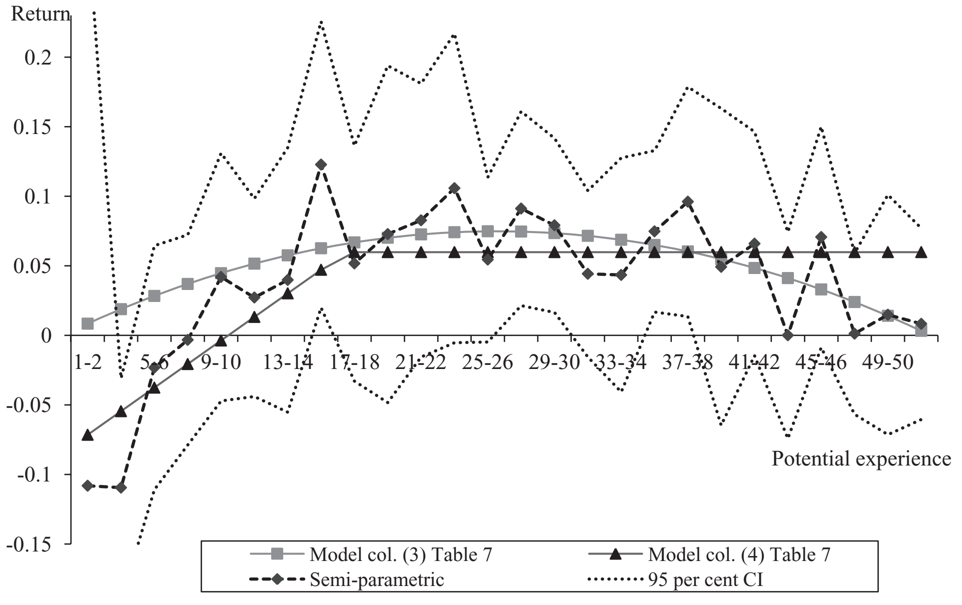


Figure 7. The effect of early cognitive ability over the life-cycle, semi-parametric and parametric models. Dependent variable is log yearly earnings for women



Note: The semi-parametric model includes dummy variables for experience as indicated, in addition to the control variables in the models in Table 3.

Table 7. The effect of cognitive ability over the life-cycle. Dependent variable is log yearly earnings of women

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	**All**	**All**	**All**	**All**	**Working full time**	
Early cognitive ability	0.051**	0.055**	–0.064~	–0.084*	0.014	–0.017
	(0.014)	(0.024)	(0.033)	(0.035)	(0.022)	(0.022)
Interaction between 'Early cognitive ability' and						
Potential experience/100	—	–0.014	0.990**	—	0.280	—
		(0.073)	(0.295)		(0.216)	
Potential experience squared/100	—	—	–0.0171**	—	–0.0038	—
			(0.0051)		(0.0038)	
Potential experience/100. Linear to 17, constant thereafter	—	—	—	0.547**	—	0.473**
				(0.251)		(0.190)
Test for joint significance of 'Early cognitive ability' at level and interactions, p-value	<0.001	0.001	0.001	<0.001	<0.001	<0.001
R^2	0.5714	0.5714	0.5723	0.5720	0.2961	0.2964
Observations	5,586	5,586	5,586	5,586	3,937	3,937

Notes: Same model specification as in Table 3, except as indicated. The education main effects are absorbed by the experience and year dummy variables.
~, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

Table 8. Vocationally versus academically educated. Dependent variable is log yearly earnings for women

	(1)	(2)	(3)
B. Vocational education			
Early cognitive ability	0.024	–0.042	–0.045
	(0.016)	(0.040)	(0.043)
Interaction between 'Early cognitive ability' and			
Potential experience/100	—	0.630~	—
		(0.343)	
Potential experience squared/100	—	–0.0115*	—
		(0.0058)	
Potential experience/100. Linear to 17, constant thereafter	—	—	0.429
			(0.306)
Test for joint significance, p-value	0.145	0.150	0.259
R^2	0.5513	0.5518	0.5514
Observations	4,058	4,058	4,058
C. Academic education			
Early cognitive ability	0.106**	–0.186**	–0.189**
	(0.030)	(0.064)	(0.062)
Interaction between 'Early cognitive ability' and			
Potential experience/100	—	2.323**	—
		(0.611)	
Potential experience squared/100	—	–0.0388**	—
		(0.0117)	
Potential experience/100. Linear to 17, constant thereafter	—	—	1.865**
			(0.457)
Test for joint significance, p-value	0.001	<0.001	<0.001
R^2	0.6139	0.6175	0.6170
Observations	1,528	1,528	1,528

Notes: Same model specification as in Table 3 columns (1), (3) and (4), except as indicated. The education main effects are absorbed by the experience and year dummy variables.
~, * and ** denote significance at 10, 5 and 1 per cent level, respectively. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

Table 8 distinguishes between individuals with vocational and academic education. Similar to the model for men, the average return to ability is highest within the group that is academically educated. The return to cognitive ability for women with vocational training is insignificant, although it seems to be non-linear. For the sample with academic education, the return to ability is estimated to be highly non-linear.

4.6. *The speed of learning*

The idea in the employer learning literature is that employers learn about workers' unobserved productivity by observing actual productivity. This section estimates Lange's (2007) parameter 'the speed of employer learning', which is a parameter for how fast the market learns.

A noisy signal y_{it} of actual productivity f_{it}, conditional on the experience profile $h(x_{it})$, is given by

$$y_{it} = f_{it} - h(x_{it}) + v_{it}. \quad [4]$$

The lower the variance of the noise v_{it}, the faster employers (and employees) learn about the true productivity. The literature assumes that v_{it} is independently, identically, and normally disturbed with constant variance σ_v^2. The normality assumption implies that the expectation of true productivity is a weighted average of all signals plus the expected productivity from equation [2] above. Lange (2007) shows that the weights are given by

$$\theta_x = \frac{xK}{1+(x-1)K} \quad \text{and} \quad (1-\theta_x) = \frac{1-K}{1+(x-1)K} \qquad [5]$$

respectively. $K = \sigma_0^2/(\sigma_0^2 + \sigma_v^2)$ is the parameter for the speed of learning, where σ_0^2 is the variance of the initial expectation error of productivity, i.e. the expectation error of equation [2] for $x = 0$.

The parameter K reflects the relative information content of the initial information (education in our model in equation [1]) and subsequent measurements y_{it}. The smaller the parameter K, the less information is provided by new signals. Thus, the weight θ_x on the signals is increasing in experience x and decreasing in the size of the noise σ_v^2 relative to the initial expectation error σ_0^2.

Lange (2007) proposes a two-stage approach to estimate K. First, estimate the model in equation [3] without restrictions. That is a model where ability and schooling are interacted with a full set of experience dummy variables D_x

$$w_{it} = \sum_x a_x Z_i * D_x + \sum_x b_x S_i * D_x + b'_\Phi \Phi_{it} + \varepsilon_{it}, \qquad [6]$$

where Φ_{it} is a vector of control variables. For reasons described above, the present paper focus only on the effect of ability, and thus we analyse the information contained by the parameters a_x. The second stage fits the following relationship with non-linear least squares.

$$a_x = \phi_x a_\infty + (1-\phi_x) a_0 = \frac{xK}{1+(x-1)K} a_\infty + \frac{1-K}{1+(x-1)K} a_0, \qquad [7]$$

where a_∞ and a_0 are the effects of ability when $x \to \infty$ and $x = 0$, respectively. There is a smooth transformation in the relationship between wages and early cognitive ability from the case without experience to the case when all possible signals have arrived.

Table 9 presents estimation results. For men, the speed of learning is 0.22, which is close to Lange's (2007) estimate of 0.23. Notice that our model includes the life-cycle return (51 observations) in contrast to Lange who only include up to 16 years of experience. Taken at face value, the estimate implies that $\theta_x = 0.5$ for $x = 3.5$, i.e. the average expectation error has declined by 50 per cent after 3.5 years of experience. After 17 years of experience, for which our piece-wise linear regression indicates no more learning, the expectation error amounts to 17 per cent of the initial expectation error. The estimate is, however, clearly insignificant.[27] Comparing the scatterplot of the effects of ability at different experience levels in Figure 4 above with Lange's (2007, Figure 2) scatterplot, there is clearly larger variation in the point estimates in our case. Figure 4 shows a modest increase in the return to ability over the first 10–14 years of experience, whereas Lange (2007) and Arcidiacono *et al.* (2010) find a rapid increase for the first 3–4 years of experience.

The speed of learning related to IQ at age 20 is of similar size, as shown in column (2) in Table 9. The parameter for women of 0.15 [column (3)] implies that the average expectation error has declined by 50 per cent after 6 years of experience. Notice, however, that all the

Table 9. The speed of employer learning

	(1) Men, early cognitive ability	(2) Men, IQ at age 20	(3) Women, early cognitive ability
Speed of employer	0.221	0.192	0.149
learning K	(2.45)	(0.354)	(0.364)
Initial value a_0	0.014	–0.054	–0.034
	(0.279)	(0.158)	(0.110)
Limit value a_∞	0.039	0.096**	0.074~
	(0.023)	(0.026)	(0.038)
Observations	51	51	52

Notes: Nonlinear least squares estimation based on equation [7] using coefficient estimates on ability at the different experience levels.
~, * and ** denote significance at 10, 5 and 1 per cent level, respectively.

estimates for the speed of learning are highly imprecise. On the other hand, the estimates of a_∞ indicate that the models give a reasonable description of the learning process. In all three models, the estimate of a_∞ is close to the estimate for experience above 20 years as reported in Figures 4, 5 and 7 above.

4.7. Cognitive ability and supervisory positions

Demonstrated competence and productivity is often a premise for promotion to more influential positions. The return to cognitive ability may increase in experience because promotions to leader positions are more likely among high-ability individuals. From the questionnaires in 1964, 1971 and 1984 we have information on whether the individuals have supervisory positions. The information is available for 92 per cent of the individuals included in the earnings equations. A rising share of the sample has a supervisory position, increasing from 28 per cent in 1964 to 32 per cent in 1971 and 39 per cent in 1984.

We investigate whether the variable 'Early cognitive ability' influences the probability of having a supervisory position by estimating linear probability models with the same specification as the earnings equations. Table 10 presents the results. One standard deviation in early cognitive ability increases the probability of having a supervisory position by 3.2 per cent for men and 2.6 per cent for women. The effect is significant at the 10 per cent level for men. The effect seems to be larger for the academically educated than for the vocationally educated, but is not statistically significant for either of the groups.[28]

Can the return to ability in terms of earnings be explained by promotions to supervisory positions? To investigate this question, we first run the conditional earnings model on the sample with information on supervisory positions, and next add the dummy variable for supervisory position. The difference in return to ability between these two models turns out to be rather small; the estimate decreases from 0.027 to 0.021 for men and from 0.040 to 0.033 for women. Thus, promotions to supervisory positions explain only a small part of the return to cognitive ability, although the return to supervisory positions is 0.17 and 0.26 log points for men and women, respectively.

Table 10. Ability and leader position. Dependent variable is whether the individual is a supervisor

	(1) Men	(2) Vocational education, men	(3) Academic education, men	(4) Women
Early cognitive ability	0.032~	0.019	0.042	0.026
	(0.018)	(0.022)	(0.033)	(0.016)
R^2	0.1208	0.0694	0.0899	0.0826
Observations	1,562	1,060	502	945

Notes: Data from the questionnaires in 1964, 1971, and 1984. In addition to early cognitive ability, the models include: a cubic of potential experience, three dummy variables for educational type, marital status, year specific effects, an imputed dummy variable for part-time work, and a dummy for early retirement. All variables are interacted with potential experience.
~ denotes significance at 10 per cent level. Standard errors in parentheses are corrected to account for within-individual clustering of errors.

5. Conclusion

We estimate the return to cognitive ability at age 10 on earnings at ages 20–65 for a Swedish cohort. Over the life-cycle, the average unconditional return to one standard deviation of early cognitive ability is about 20 per cent, but our results clearly indicate that most of the effect goes through educational choices. The average return conditional on, inter alia, education and experience, is only about 4 per cent.

We find that the conditional return to early cognitive ability increases the first 15–25 years after finishing school. This result is in accordance with the hypothesis that cognitive ability is revealed by the labor market as workers gain experience. It seems that no more learning takes place after 25 years. We find that the return to early cognitive ability over the life-cycle is similar for men and women, but highest for individuals with academic education. Cognitive ability seems to have a positive impact on the probability of being employed in a leader position, but this effect explains only a small part of the return on earnings.

We find lower conditional returns to cognitive ability than is typically found in other studies. The difference may be partly related to the types of skills being tested and the timing of the tests. Previous studies have used the AFQT score in the NLSY, which are conducted after schooling choices are made. When schooling choices affect test scores, the return reflects both early cognitive ability and individual educational choices. Thus, the return to cognitive ability may be overestimated in the sense that it partly includes the return to education.

We leave to future research the question of why the return to cognitive ability is increasing in experience. Market learning is only one potential explanation. Hause (1972) argues that experience and cognitive ability are complements in producing earnings because ability increases the capacity to acquire job-relevant skills and more complex skills, and enables workers to use these skills. Lillard (1977) finds the same wage dynamics as the more recent employer learning literature, but interprets the results within a life-cycle human capital theory with inter-temporal choices of investment in earnings potential. Access to, or benefits from, on-the-job-training may depend on learning capacity.

Notes

[1] See Farber and Gibbons (1996), Altonji and Pierret (2001), Lange (2007), Schönberg (2007), Pinkston (2009), and Arcidiacono *et al.* (2010) for more detailed descriptions of market learning processes.

[2] Altonji and Pierret (2001) derive predictions of how $\partial A/\partial x$ and $\partial B/\partial x$ are related and how $\partial B/\partial x$ depends on whether $A(x)$ is controlled for or not. A crucial assumption for the prediction $\partial B/\partial x \leq 0$ is that the effect of education on productivity is non-increasing as in equation [1] above. A further discussion is left out here because our focus is on $A(x)$.

[3] The data are described in more detail in Husèn (1950) and Sandgren (2005).

[4] During the empirical period, Malmö was the third most populous city in Sweden. The municipality consists of mostly urban areas, but also some rural parts. Manufacturing used to be an important part of the local economy, and one of the world's largest shipyards was located in the city in the 1950s and 1960s. Malmö was hit relatively hard by the recession in the 1970s, and the population fell from 265,000 inhabitants in 1971 to 229,000 in 1985. Since 1995, regional economic growth has been relatively high, probably as a result of the new bridge across the Öresund that has made Copenhagen–Malmö an integrated economic area.

[5] Because the sample is based on third graders, the students do not necessarily need to be born the same year. In the data, 86.0 and 88.3 per cent of the boys and girls, respectively, are born in 1928, 12.2 and 9.7 per cent are born earlier and 1.8 and 2.0 per cent are born later. The large number of over-aged students is probably due to class repetition.

[6] These girls had average scores on the other cognitive ability measures.

[7] Earnings register data are collected in 1948, 1953, 1958, 1963, 1968, 1969, 1971, 1974, 1978, 1982, 1986, 1990, and 1993. We do not have information on hours of work, hence not on part-time work. The problem of having data on annual earnings instead of hourly earnings is likely to be most pronounced for women because they work part-time to a much larger degree than men. Among the men, part-time jobs were rare. What might occur, though, is that some individuals did not work the whole year, because of, e.g. shorter spells of unemployment or seasonal work. The unemployment rate in Sweden was extremely low up to the 1990s, averaging about 2 per cent. In the empirical analysis, we include a dummy variable for earnings clearly below full-time, full-year wage, including 5.4 per cent of the observations for men and 29.5 per cent of the observations for women. The share of part-time workers is constant over time for men, but it is decreasing for women. In the questionnaire in 1984, 95 per cent of the men reported that they had full-time work.

[8] The attrition seems to be largest in 1953. The number of observations in 1953 is 28 per cent below the number of men who reported working in 1953 in the questionnaire in 1964. The corresponding number for 1948 and 1958 is 18 and 11 per cent, respectively. We have run all the regressions in Table 3 on only those men for whom we have earnings information in 1948 and 1953, to see if these men are representative of the dataset as a whole. The results are very similar, with very marginal differences on the coefficients.

[9] For 1968, the Malmö data include more individuals than the data from Statistics Sweden, but the opposite is true for 1971. Thus, in the empirical analysis we use the Malmö data up to 1969 and data from Statistics Sweden from 1971. In the original Malmö study, earnings are reported in thousand SEK. In 1948 there are 13 earning levels in the data, but in 1969 there are 106 earning levels. From 1971 and onward, the precise earning is reported and includes taxable benefits such as unemployment benefits. Before 1971, benefits were not taxable and thus not registered in the tax registers.

[10] In 1982, the average earnings for men in the sample is 103,000 SEK with a standard deviation of 59,000. According to Statistics Sweden, the average earnings in 1982 of all men in Sweden born in 1928 was 93,000 SEK with a standard deviation of 66,000. The slightly higher average wage in the Malmö data is likely due to lower wages in rural than in urban areas.

[11] The standard deviation of log earnings for men varies from 0.45 to 0.65, and is lowest in the 1950s and highest in 1968 and 1986. The standard deviation is larger for women, probably due to more part-time work and varying labor supply over the time period. For both genders, there is an increasing

trend in the standard deviation up to about 1970. Thereafter the standard deviation is about 0.6 for men and about 0.9 for women.

[12] When calculating actual experience, we have made some assumptions. For the period up to 1951, we have assumed that the individuals entered the labor market when they finished their education, if information from the questionnaire in 1964 is missing. For the period after 1951, we have assumed, if information is missing, that the individual is working if he worked the previous year. Nevertheless, we have missing values for 24 and 28 per cent of the observations for men and women, respectively. Those who have not answered the questionnaires have somewhat lower scores on the ability measures and less education and earnings than those who returned the questionnaires, although the differences are quite small. The correlation coefficient between actual and potential experience is 0.95 for men, reflecting high employment probability among the men in the empirical period. For women, the correlation coefficient is 0.70.

[13] The educational types requiring 12 years of schooling were typically female-dominated professions such as hospital nurses.

[14] The number of men and women, respectively, included in the analysis is 259 and 241 in 1948, 354 and 308 in 1953, and 478 and 259 in 1958. Thereafter, there are 630–700 observations of men, except in 1993, with 589 observations. For women, the number of observations increases about linearly from 1958 to the mid 1970s, and is about 530 thereafter.

[15] Heckman and Vytlacil (2001) make the point that, if the relationship between education and cognitive ability tests becomes too strong, it is impossible to disentangle the effects of education and ability tests. In our data, individuals with highest cognitive ability are distributed across all types of schooling.

[16] The return to early cognitive ability is lowest in 1986. It seems that the few observations of part-time work (5 per cent) have a specific impact in 1986. Excluding observations of part-time work, the return to ability is about the same in 1986 as in the surrounding years.

[17] The difference in the return to education is significant at the 5 per cent level in all years except two.

[18] This estimate cannot directly be interpreted as the mean of a random individual because the attrition is lower in the start of the empirical period. Thus, the mean individual return is expected to be lower. Using weighted regression with the inverse of the number of observations for each level of potential experience as weight, the average return is estimated to 4.0 per cent.

[19] One may be concerned that the decline in the return to early cognitive ability in the last years of the working life observed in Figure 4 came about by the overall compression of the wage distribution that took place in Sweden during the 1970s. The compression is typically related to increased union strength under a highly centralized wage bargaining regime (see, e.g. Hibbs and Locking, 1996), although Edin and Holmlund (1995) argue that a substantial part of the relative pay movements can be explained by demand and supply factors. If union influence has changed over time, it may be difficult to interpret the interaction effect between ability and experience because, to some extent, the effect of ability at different experience levels is identified at different points in time. However, Figure 4 indicates low return to ability for potential experience of 37–44 years. In our sample, individuals with only primary education (i.e. those who entered the labor market first) had potential experience of 37 years in 1980, at the end of the period of wage compression in Sweden. The low return to ability for potential experience of 37–44 years therefore can hardly be related to the overall wage compression in the 1970s. Falch and Sandgren (2008) estimate models using the rank in the wage distribution as the dependent variable, a variable that is less sensitive to overall changes in the density of the earnings distribution, but the results clearly indicate that the compression of the wage distribution in the 1970s does not affect the estimated return to ability over the life-cycle.

[20] Excluding the main effect, which clearly cannot be rejected in statistical terms, does not change the estimates of the interaction effects, but makes both interaction terms significant at the 5 per cent level. We have also estimated models including interaction with the third polynomial of potential experience. Then, all interaction effects have low precision.

[21] The studies using NLSY identifies the effect of education on individuals who obtain education after they have started their working career. That is not possible with the present data because information on education is based on a questionnaire at age 36 and on data from public registers.

[22] See Falch and Sandgren (2008) for detailed results regarding potential versus actual experience and for other model specifications of potential experience.

[23] The average value of the variable 'Early cognitive ability' differs between the groups. Average ability is –0.31 (0.97) for individuals with vocational education and 0.80 (0.81) for academic education (standard deviations in parentheses).

[24] If observations with potential experience above 44 years are excluded from the model, the results of all model specifications where ability is measured by IQ in third grade are very close to the results for the models with the compound ability measure in Table 3, including the average return.

[25] Papers using other data-sets find the same effect; see e.g. Griliches and Mason (1972), Griliches (1976), Winship and Korenman (1997) and Hansen *et al*. (2004).

[26] The correlation coefficient between actual and potential experience is 0.70 for women, clearly lower than for men. However, by simply replacing potential experience with actual experience, the estimated coefficients change only marginally, see Falch and Sandgren (2008).

[27] We have estimated several alternative models formulations, including bootstrapping of standard errors, models using the inverse of the standard errors of the left hand side variables as weight, and models excluding the observations with high experience levels. All models yield clearly insignificant estimates of the speed of employer learning *K*.

[28] We have also investigated the effects of the separate ability measures on the probability of having a supervisory position. Only the IQ measures have a significant effect at the 10 per cent level. For men, we find an effect of 3.5 and 9.0 for IQ measured in third grade and at age 20, respectively, but for women the effect of IQ in third grade is 2.4.

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