Does the apprenticeship system affect employer learning? Evidence from Switzerland

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Abstract

According to theoretical models of employer learning, education is an important signal to the employer. As the employer obtains gradually better information on the productivity of workers, the returns to schooling should decrease over time while the returns to initially unobserved characteristics should increase simultaneously. In this study, we test these theoretical predictions by using data from the Adult, Literacy and Lifeskills survey (Swiss sample). Based on earlier results on Germany, it has often been argued that employer learning should be less important in countries where the apprenticeship system is predominant. Thus, the Swiss case offers an opportunity to check the validity of this claim. We make use of literacy scores and find that the return to skills (vs. the returns to formal schooling) increase with experience while the reverse is true with respect to formal education. Our results suggest that employer learning takes place in Switzerland and indicate

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that the apprenticeship systems may not provide more accurate information on the true productivity of workers.

1 Introduction

The prevalence of the signaling model is a question of primary importance as one wants to determine what drives the returns to formal education. The traditional test of the signaling model against the human capital model relies on the hypothesis that the effect of education on earnings will decline with experience as employers gradually get a more accurate measure of their workers' productivity. The relationship between the returns to schooling and labour market experience has been investigated in the US by Farber and Gibbons (1996) and Altonji and Pierret (1998, 2001), in Germany by Bauer and Haisken-DeNew (2001) and in the UK by Galindo-Rueda (2003). These studies rely on a similar empirical strategy that consists in investigating jointly the returns to formal education and ability, and the dynamic of these variable with labour market experience. If the signaling model has any relevance, the returns to formal education should be independent to labour market experience or could even decrease. On the other hand, the returns to ability should increase with time as the employer learns about the true productivity of his/her employees.

In this paper, we attempt to test the employer learning hypothesis with data from the Swiss sample of the Adult, Literacy and Lifeskills survey (ALL) of 2003. We measure ability by means of literacy scores. We argue that literacy variable better capture natural ability than other variables used in the literature such as parents' education. The focus on the Swiss case is also quite interesting because of the importance of the apprenticeship system in this country. Indeed, Bauer and Haisken-DeNew (2001) explain the lesser importance of employer learning in Germany compared to the US by the prevalence of the apprenticeship in Germany. The rationale is that apprenticeship provides a standardized form of education which in turn provides more accurate information on the productivity of workers. In this light, Switzerland provides an interesting international comparison. Our results point to evidence of employer learning for Swiss males. The returns to formal education decrease with labour market experience while the returns to ability increased with experience. Our results also show that there is no returns to ability independently from labour market experience. However, we can not rule out the possibility that our results are driven by other explanations than the employer learning model.

The remainder of the paper is organized as follows: Section 2 presents the employer learning model while Section 3 describes the data. Section 4 discusses the results and Section 5 provides concluding comments.

2 Employer learning model

In order to test the signaling model against the human capital model, the traditional approach has been to investigate the dynamic relationship between the return to formal education and labour market experience. Falling returns with experience should validate the signaling model, as employers obtain better information on the true productivity of their workers (see Weiss, 1995).

As Bauer and Haisken-DeNew (2001), we borrow heavily from Altonji and Pierret (1998, 2001).[1] We suppose that wages are given by the following equation:

$$\log(Y_{iT}) = H(T_i) + \beta_S S_i + \beta_{ST}(S_i.T_i) + \beta_L L_i + \beta_{LT}(L_i.T_i) + u_{i,T} \qquad (1)$$

where Y_{iT} is the wage of worker i with T years of labour market experience, $H(T_i)$ is the experience profile of productivity, S_i is defined as the year of formal education and L_i refers to an indicator of natural ability of the workers. The latter is assumed to be observed by the econometrician but not by the employer at the beginning of the working life. According to Altonji

[1] The latter built upon the seminal work from Farber and Gibbons (1996).

and Pierret (1999, 2001), $\beta_{ST} = \beta_{LT} = 0$ if employers have full information on their workers' productivity or they do not learn over time. This model allow S and L to be correlated with each other, which implies that β_{ST} may be negative as the schooling variable initially captures some ability effects. In the meantime, β_{LT} should be positive as employers obtain gradually the information about L. Going a step further, Altonji and Pierret (2001) show that the relation between β_{ST} and β_{LT} can be stated as follows:

$$\beta_{ST} = \Phi_{LS}\beta_{LT} \tag{2}$$

where Φ_{LS} is the regression coefficient of L_i on S_i. As Φ_{LS} can easily be estimated, equation (2) provides a statistical test of employer learning. Equation (2) comes from the fact that the pattern of β_{ST} stems from the relationship between literacy and formal education. Indeed, it is because formal education and skills are correlated with each other, while formal education is part of the initial information of the firm, that the effects of literacy will spill over the coefficient attached to formal education. As firms could discriminate between workers on the basis of other information than skills, proposition (2) may not hold. This would not mean that employer learning is inexistent in our data. However, it could indicate that alternative explanations for the behavior of β_{ST} and β_{LT} may be considered.[2]

As β_{SL} captures information on workers' productivity, it would be interesting to assess whether this information is public or private. Equation (1) implicitly assumes that all the information on the productivity of a worker is public. Bauer and Haisken-DeNew (2001) distinguish between private and public information by splitting the experience terms between job tenure and labor market experience prior he/she started to work for the current firms. Thus, the model becomes:

[2] If our literacy variables do not entirely capture the skills required by the firms, one would expect $\beta_{ST} > \Phi_{LS}\beta_{LT}$. Such result would not mean that the employer learning model is not relevant at all. Yet, it would mean that alternative explanations could be put forth.

$$\log(Y_{iT}) = H(T_i) + \beta_S S_i + \beta_{St}(S_i.t_i) + \beta_{ST-t}(S_i.(T_i - t_i)) \\ + \beta_L L_i + \beta_{Lt}(L_i.t_i) + \beta_{LT-t}(L_i.(T_i - t_i)) + u_{i,T} \quad (3)$$

where t_i indicate job tenure with the current firm. If information on individual productivity is private, we have $\beta_{Lt} > \beta_{LT-t} = 0$ and $\beta_{St} > \beta_{ST-t} = 0$ as the return to ability and schooling should only be affected by the experience with the current employer. On the other hand, $\beta_{Lt} = \beta_{LT-t}$ and $\beta_{St} = \beta_{ST-t}$ would mean that the information is public, i.e. the return to ability and schooling being independent from the way experience is measured. Equation (1) and (3) are estimated by means of standard OLS regressions as well as by means of quantile regressions. The latter allows to test the model at different point of the wage distribution.

3 Data and choice of variables

In this study, we make use of the Swiss sample of the Adult, Literacy and Lifeskills survey (ALL). ALL is an international survey conducted in 7 countries (United States, Norway, Canada, Bermudas, Italy, the State of Nuevo Leon in Mexico and Switzerland) under the supervision of Statistics Canada and the support from the OECD. These data contain numerous information on jobs, socioeconomic backgrounds and literacy level of the individuals. In this study, we focus on male employees aged between 20 and 65 years. We leave out women as we do not have enough information on carreer interruptions, which is an important element to take into account with respect to the dynamic pattern of education and literacy skills. We discard individuals that are still completing education. After deleting for missing variables, we end up with a sample of 1255 observations.

Our key variable is the measured ability of the workers. In the data, various forms of literacy have been assessed: prose, document reading, numeracy and problem solving. However, information on the latter skill is

Table 1. Weighted descriptive statistics: selected variables

Variables	Mean	S.D.
Hourly wage (log)	3.6056	0.4871
Years of schooling	14.53	3.188
Experience	21.86	12.22
Job tenure	11.49	10.98
Firm sponsored training	0.3608	0.4802
Professional training	0.4393	0.4963
Supervising duties	0.4900	0.4999
Single individual	0.1242	0.3299
Born in a foreign country	0.1477	0.3548
Half or more education in Switzerland	0.8850	0.3190
Firm size dummies		
1-19	0.2338	0.4232
20-99	0.1866	0.3896
100-499	0.2094	0.4068
500-999	0.0766	0.2659
1000 and more	0.2937	0.4554

Source: Adults Literacy and Lifeskills survey (Swiss sample) 2003
1255 observations

missing for a substantial proportion of the sample. Thus, our measure of ability is the sum of the three remaining skills. The skill variable is standardized, thus its standard deviation is equal to one and its mean is equal to zero. A problem would arise if skills could be obtained through labour market experience. In a context of political concern about skill deterioration, this seems quite unlikely. Actually, our measure of skills is negatively correlated with labour market experience. The latter variable is defined as potential experience i.e. age minus 6 minus the years of education. We also compare the literacy scores with the reported education level of the parents, as this variable was used in a comparable study on Germany (Bauer and Haisken-DeNew, 2001). While the two variables are highly correlated, the level of the correlation highly depend on the age of the respondents. Indeed, the correlation between parents' education and literacy decreases with age, which indicates that parents' education may be a relatively poor proxy for ability with respect to older individuals.

The dependent variable is the log of the hourly wage. The dependent variables of primary interest are education (in years), literacy, experience modeled with a cubic polynomial, the interactions between experience and education and the interaction between experience and literacy skills. We also include a large set of control variables in our specification: 9 occupation dummies, 11 industry dummies, 5 regional dummies, 4 firmsize dummies, a single person dummy and a set of dummies pertaining to the immigration status. Job related dummies are introduced as a problem may arise if the information to employers depend on the type of job. We also control for the impact of on-the-job training. As noted by Altonji and Pierret (1998, 2001), β_{ST} and β_{LT} could be positive if education and ability are positively correlated with access to on-the-job training. Regarding Switzerland, Gerfin (2004) points to some positive selection into on-the-job training as the effects of training becomes much smaller when correcting for selection bias. Our training variables are build upon a set of question pertaining to the availability of training, the type of training and who paid for it. Thus, our on-the-job training variable takes the value of one if the respondent received firm-financed training during the year prior to the interview. We also include another dummy variable for any professional training, whether it has been financed by the firm or by the individual. Weighted descriptive statistics of the sample are reported in Table 1.

4 Results

4.1 OLS estimates

We first report the results from the OLS regressions (Table 2). Three specifications are displayed: the first one includes the years of schooling variable, the literacy scores and the interaction between schooling and experience (column 1). The second specification corresponds to equation (1), i.e. both schooling and ability scores are interacted with the experience (column 2). Finally, the third model decompose total experience between tenure with the current firm and public experience, that is labour market experience prior to the current job (column 3).

Our results show a positive correlation between education and hourly wages. According to the basic specification (column 1), the return to an additional year of schooling is equal to 5.5% at the sample mean of 21 years of experience. The relatively small size of this rate of return can be partially explained by the inclusion of literacy scores, a variable that tend to decrease the schooling estimates (see Green and Riddell, 2003). Indeed, when we remove the literacy variable, the return to an additional year of schooling are equal to 6%. Regarding the interaction term between schooling and labour market experience, we note that the related coefficient is negative and statistically significant. This means that the return to schooling decrease with labour market experience by approximately 0.08% for each additional year of experience. This might be considered as early evidence of employer learning. An alternative interpretation could be the gradual obsolescence of human capital, as the skills obtained in the past do not match current requirement anymore.[3] Finally, the literacy score variable is positive and statistically significant. At the sample mean, one additional standard deviation in literacy scores implies a wage gain of approximately 6%.

In a second step, we introduce an interaction term between measured ability and labour market experience. The schooling coefficient and the coefficient attached to the interaction term between schooling and experience become larger in absolute value. This means that the returns to schooling at labour market entry are now larger while the return to an additional year of education at sample mean remain broadly unchanged. Regarding the literacy coefficients, we observe that there is no return to literacy at labour market entry as the coefficient attached to the literacy score is negative and non significantly different from zero. On the other hand, the return to literacy increase with labour market experience as the interaction term is positive and statistically significant. For instance, after ten years of experience, one additional standard deviation of literacy score brings a wage gain of approximately 3%. Thus, our results are consistent with employer learning as

[3] see Ramirez (2002) for details on this topic in the Swiss context.

Table 2. OLS estimates, earning functions

	(1)	(2)	(3)
Education	0.0548 (5.96)	0.0619 (6.32)	0.0590 (6.43)
Literacy score (standardized)	0.0604 (4.20)	-0.0049 (-0.15)	-0.0463 (-1.44)
Education*Experience	-0.0008 (-2.18)	-0.0011 (-2.82)	-
Literacy score*Experience	-	0.0029 (2.38)	-
Education*(Experience-Tenure)	-	-	-0.0018 (-3.87)
Education*Tenure	-	-	-0.0002 (-0.66)
Literacy score*(Experience-Tenure)	-	-	0.0067 (4.61)
Literacy score*Tenure	-	-	0.0024 (1.80)
R^2	0.4050	0.4084	0.4133

Note: The dependent variable is the log of hourly wages. Between brackets: t-values computed from robust standard errors. All equations include the following control variables: 10 occupation dummies, 4 firmsize dummies, 11 industry dummies, binary variables for single person, born in Switzerland, studies in Switzerland, supervisor, professional training, firm's financed professional training. Tenure and experience are modeled with a cubic polynomial. 1255 obs.

proposed by Altonji and Pierret (1998, 2001). This view is even strengthened by the fact that there is not return to literacy skills independently from labour market experience. This may indicate that literacy is rewarded only once employers can measure the true productivity of their employees.

However, as proposed by Altonji and Pierret (2001), one can perform a test that provides some leverage in differentiating between the employer learning interpretation and alternative stories for our results. According to (2), the negative of the coefficient of the regression of literacy skills on schooling time the coefficient on the interaction between literacy and experience should equal the coefficient on the interaction between formal education and experience. The product is equal to -0.0004 while the coefficient on column 2 is equal to -0.0011. A Wald test rejects equation (2) (p-value=0.05). This means that we can not rule out that an alternative explanation best explain the pattern of the coefficients attached to variables interacted with experience. The fact that the product is smaller that the coefficient attached to the interaction term between formal education and experience may indicate that our literacy variable do not capture the whole information flows towards the firm. Alternatively, one may think that the information flow to the firms differs depending on the type of occupation, mitigating the impact of the literacy variable. In this case, the inclusion of occupational dummies may innaccurately account for this problem as it would implicitly assume that the time pattern of the returns to literacy skills is the same throughout occupations. We will come back to this issue in one of the following section of this article.

As per Bauer and Haisken-DeNew (2001) and Galindo-Rueda (2003), we attempt to decompose total experience between tenure and experience prior current employment. The goal is to test wether the information on the workers' productivity is private or rather public. Our results seem to indicate that the information is public as well as private. However, we can note that coefficient attached to public information (the interaction between public experience and ability) is significantly greater that this attached to private information (the interaction between tenure with current job and ability). Such result is at odds with those of Bauer and Haisken-DeNew (2001), as they found that the information on workers' productivity was rather private. The results of Galindo-Rueda (2003) are more ambigous, though they point to some evidence of private learning for blue collar workers.

4.2 Quantile regressions

We next turn to the estimation of employer learning by means of quantile regression. This technique enables to analyze the impact of independent variables at different levels of the wage distribution. In our case, this feature may prove quite important as OLS estimates may overlook differences between low paid and high paid workers. Indeed, there is many reasons to believe that employer learning might be more relevant at the low end of the distribution. As wages grow, employer may have more incentives to screen their employees at time of hiring. Moreover, as pointed out by Bauer and Haisken-

Table 3. Quantiles regression estimates, earning functions

Quantile	0.25	0.50	0.75
Total information			
Education	0.0449 (4.02)	0.0547 (6.56)	0.0531 (5.32)
Literacy score (Standardized)	0.0067 (0.22)	0.0224 (0.86)	0.0279 (0.91)
Education*Experience	-0.0008 (-1.78)	-0.0009 (-2.66)	-0.0008 (-1.77)
Literacy score*Experience	0.0031 (2.54)	0.0015 (1.53)	0.0016 (1.21)
Pseudo R^2	0.2895	0.3103	0.3038
Public vs. private information			
Education	0.0329 (3.71)	0.0453 (5.92)	0.0461 (4.77)
Education*(Experience-Tenure)	-0.0010 (-1.99)	-0.0013 (-2.96)	-0.0012 (-3.14)
Education*Tenure	0.0003 (0.78)	-0.0000 (–0.06)	0.0003 (0.65)
Literacy score (Standardized)	0.0107 (0.38)	-0.0068 (-0.29)	-0.0065 (1.22)
Literacy score*(Experience-Tenure)	0.0035 (2.83)	0.0042 (3.07)	0.0048 (2.89)
Literacy score*Tenure	0.0016 (1.17)	0.0020 (1.88)	0.0005 (0.36)
Pseudo R^2	0.2857	0.3057	0.3077

Note: The dependent variable is the log of hourly wages. Between brackets: t-values computed from bootstrapped standard errors (100 repetitions). All equations include the following control variables: 10 occupational dummies, 4 firmsize dummies, 11 industry dummies, binary variables for single person, born in Switzerland, studies in Switzerland, supervisor, professional training, firm's financed professional training. Experience and tenure are modeled with a cubic polynomial. 1255 observations.

DeNew (2001), occupations may differ in the way the employer obtains the information about workers' productivity. For instance, for some occupations, productivity is easily measurable while it is not the case in others. Bauer and Haisken-DeNew hypothesize that the productivity of blue-collar workers is easier to measure, as employer learning seems to take place only in this category of worker in Germany.

We report the results of the quantile regression in Table 3. We can observe that the estimated coefficients are quite consistent throughout the wage distribution. The return to education are broadly similar at the various point of the wage distribution as the differences between the coefficients are not statistically significant.[4] The coefficient attached to the interaction term between literacy and experience is bigger at the low end of the distribution, which is in line with theoretical expectations. Yet, the differences between

[4]The statistical tests are not reported and are available upon request.

quantiles fails to be significant at any conventional level. We can also note that for each quantile, the information on workers' productivity seem to be predominantly public. At the 25th and 75th percentiles, the private information coefficients even fail to be statistically different from zero.

4.3 Results by subgroups

While our results suggest that employment learning takes place throughout the wage distribution, it is also interesting to test whether our results hold for different type of occupations or jobs. Thus, we distinguish between blue collar and white collar workers, and between supervisory and non-supervisory jobs. The rationale for the first distinction is that blue collar workers may be easier to monitor, thus employers may obtain a more accurate measure of their productivity. For this reason, employer learning is more likely to be observed with respect to blue collar workers. To a lesser extent, the same line of argument could be used for the distinction between supervisory and non-supervisory jobs. A second reason to run separate estimations by type of occupation is to test whether the rejection of the proposition described by equation (2) is due the aggregation of workers from different type of occupation in the same estimation.

For the sake of brevity, we only report the estimates of equation (1) for the four groups considered (Table 4). This means we do not distinguish between public and private information. In each case, the sample size becomes quite small which makes our results at best temptative. We first note that ability is never rewarded at labour market entry as the coefficient attached to literacy skills fails to be statistically different from zero in each case. With respect to the interaction term between literacy skillls and labour market experience, we note that the coefficients are positive in each case. However, the estimates fail to be statistically different from zero for blue collar workers and for supervisor. We also test whether alternative stories could explain the dynamic pattern of the returns to literacy skills by testing equation (2) for white collar workers and non-supervisory jobs. In each case, the proposition

Table 4. Earning functions by subgroups

	Blue collar	White collar	Supervisor	Non-supervisor
	(1)	(2)	(3)	(4)
Education	0.0520	0.0664	0.0574	0.0639
	(2.91)	(5.40)	(3.69)	(4.96)
Literacy score (Standardized)	0.0271	-0.0435	0.0044	-0.0006
	(0.55)	(-1.08)	(0.10)	(-0.01)
Education*Experience	-0.0015	-0.0009	-0.0008	-0.0013
	(-2.27)	(-1.80)	(-1.38)	(-2.62)
Literacy score*Experience	0.0026	0.0042	0.0023	0.0031
	(1.38)	(2.69)	(1.35)	(1.86)
R^2	0.3427	0.3932	0.3792	0.4268
Number of observations	379	876	618	637

Note: The dependent variable is the log of hourly wages. Between brackets: t-values computed from robust standard errors. All equations include the following control variables: occupation dummies 4 firmsize dummies, 11 industry dummies, binary variables for single person, born in Switzerland, studies in Switzerland, supervisor, professional training, firm's financed professional training. Experience is modeled with a cubic polynomial.

has to be rejected at the 10% level. To conclude on this topic, the distinction between different categories of workers is more confusing than enlightening. Indeed, there is no clear pattern depending on the type of workers.

4.4 Sensitivity analysis

4.4.1 Alternative research instrument

Our results are in sharp contrast with those obtained by Bauer and Haisken-DeNew (2001) on the German case. The latter found that the employer learning hypothesis could be rejected for white collar workers while they found some evidence of employer learning for blue collar workers. One should bear in mind that this study used a different research instrument in order to capture unobserved ability i.e. the education level of the parents. In order to check wether the differences between their results and ours are driven by the choice of the independent variable, we also estimate the model by using parents' education as a measure of unobserved ability. Parents' education is measured in years of education. We use either father or mother's education,

Table 5. OLS estimates, earning functions (alternative specification)

	(1)	(2)	(3)
Education	0.0572 (6.18)	0.0567 (6.02)	0.0489 (5.76)
Parents' education	0.0007 (0.13)	0.0025 (0.21)	-0.0139 (-1.34)
Education*Experience	-0.0007 (-2.05)	-0.0007 (-1.85)	-
Parents' education*Experience*10^{-2}	-	-0.0077 (-0.17)	-
Education*(Experience-Tenure)	-	-	-0.0009 (-1.60)
Education*Tenure	-	-	-0.0000 (-0.13)
Parents' education*(Experience-Tenure)	-	-	0.0412 (0.65)
Parents' education*Tenure	-	-	0.0738 (1.73)
R^2	0.3937	0.4076	0.4048

Note: The dependent variable is the log of hourly wages. Between brackets: t-values computed from robust standard errors. All equations include the following control variables: 10 occupation dummies, 4 firmsize dummies, 11 industry dummies, binary variables for single person, born in Switzerland, studies in Switzerland, supervisor, professional training, firm's financed professional training. Tenure and experience are modeled with a cubic polynomial. 1240 obs.

whichever is greater.[5]

We display the results in Table 5. One can note that parents' educational attainment seem to have no impact on the hourly wages as the coefficients attached to this variable is close to zero (column 1). The weakness of the estimated intergenerational links may seem surprising. However, it may conceal large cohort effects as educational attainment have increased dramatically over the last decade in Switzerland (see Flückiger and Falter, 2004 or Hanslin and Winkelmann, 2006). Thus, educational attainment of the parents may imperfectly capture unobserved ability of the worker and may rather account for some historical trend, even after controlling for labour market experience. Nevertheless, one can observe that the returns to formal education decrease with labour market experience. When we interact the parents' educational attainment with experience (column 2), we once again do not find any return to parental education. Finally, the third estimation point to some positive impact of ability (measured by parents' education) as the interaction term between educational attainment of the parents and tenure is positive and statistically significant at the 10% level. Once again, the coefficients are rather small in size. One can however that according to the latter estimation, the

[5]Due to missing variables, our sample decreases in size. However, the differences between research instruments are not driven by the smaller sample.

information on the productivity of the worker is private rather than public.

The results of the alternative specifications using parents' education as an independent variable fail to be conclusive. We believe that this research instrument improperly captures the initially unobserved ability of the worker. Indeed, parents education mainly reflect cohort effects rather than differences in productivity. Thus, we feel that literacy score variable provide a better research instrument in order to test the employer learning hypothesis with our data. While differences between the present study an this of Bauer and Haisken-DeNew (2001) can easiliy be explained by the fact that they cover differents countries, the difference in the research instrument may also well explain the discrepancies.

4.4.2 Specific literacy variables

Our results could be driven by the choice of the literacy variable. In our estimation, we use the average value of the three main literacy indicators available in the date, i.e. prose, documentary and numeracy skills. As shown by Pasche (2006), different literacy skills have different impacts on labor market success in Switzerland. Thus, by taking the mean value of the three literacy indicators, one may include information on skills that are not relevant to employers. Moreover, using the specific literacy skills variable may be interesting in its own right as it may provide insights on which skill is rewarded on the Swiss labor market.

In Table 6, we report the estimates for each literacy variable. We find that the return to numeracy skills is lower than those of document or prose reading. The return to an additional standard deviation of document or prose reading is equal to 6%, while it is approximately equal to 4% in the case of numeracy. However, for each type of skills, the dynamic pattern of the variables is quite similar. This means that the interaction term between education and experience is negative while the interaction term between skills and experience is positive. The proposition embedded by equation (2) is rejected in the case of document reading and prose reading, while it is accepted

Table 6. Earning functions: specific literacy variables

Quantile	Prose	Documents	Numeracy
Education	0.0554 (5.97)	0.0561 (6.09)	0.0563 (6.19)
Education*Experience	-0.0008 (-2.27)	-0.0008 (-2.22)	-0.0008 (-2.16)
Literacy score (Standardized)	0.0595 (4.38)	0.0590 (4.54)	0.0398 (2.45)
R^2	0.4050	0.4052	0.4008
Total information			
Education	0.0622 (6.31)	0.0615 (6.53)	0.0617 (6.25)
Education*Experience	-0.0011 (-2.87)	-0.0010 (-2.80)	-0.0010 (-2.58)
Literacy score (Standardized)	-0.0030 (-0.10)	0.0002 (0.01)	-0.0002 (-0.40)
Literacy score*Experience	0.0027 (2.31)	0.0027 (2.29)	0.0025 (1.78)
R^2	0.4078	0.4081	0.4035
Public vs. private information			
Education	0.0578 (6.29)	0.0570 (6.58)	0.0581 (6.24)
Education*(Experience-Tenure)	-0.0017 (-3.55)	-0.0017 (3.71)	-0.0017 (-3.63)
Education*Tenure	-0.0003 (-0.78)	-0.0002 (-0.54)	-0.0000 (-0.25)
Literacy score (Standardized)	-0.0404 (-1.38)	-0.0416 (-1.49)	-0.0513 (-1.38)
Literacy score*(Experience-Tenure)	0.0055 (4.07)	0.0063 (4.69)	0.0068 (4.11)
Literacy score*Tenure	0.0030 (2.05)	0.0026 (1.83)	0.0012 (0.87)
R^2	0.4104	0.4125	0.4099

Note: The dependent variable is the log of hourly wages. Between brackets: t-values computed from robust standard errors. All equations include the following control variables:
10 occupational dummies, 4 firmsize dummies, 11 industry dummies, binary variables for single person, born in Switzerland, studies in Switzerland, supervisor, professional training, firm's financed professional training. Experience and tenure are modeled with a cubic polynomial. 1255 observations.

when we focus on numeracy (p-value equal to 0.35).[6] Finally, we note that for each skills, the information content seems to be public rather than private. The difference between public and private information is quite sharp with respect to numeracy skills as the coefficient attached to private information is small and fails to be statistically different from zero.

5 Conclusion

This study investigates the employer learning hypothesis by using literacy scores as indicator of true productivity. We build upon earlier paper from Altonji and Pierret (1998, 2001) and Bauer and Haisken-DeNew (2001) that focussed on, respectively, the United States and Germany. The empirical strategy consists in estimating the dynamic relationship between the returns to formal education and labour market experience. In case of employer learning, the theoretical model predicts that returns to formal education should decrease with labour market experience. On the other hand, the effect of a variable correlated with productivity, but unobserved by the employer at labour market entry, should increase with labour market experience. In our empirical test of the employer learning hypothesis, we use literacy scores as the variable correlated with unobserved ability.

Our results are broadly in line with the predictions of the theoretical model. We find that returns to education fall with labour market experience while the impact of the literacy scores grows with experience. Moreover, we find no impact of the literacy scores at labour market entry. This suggests that literacy skills are only observed on the labour market. When we decompose labour market experience between tenure with the current job and labour market experience prior to the current job, we find that information on the productivity of the workers is rather public than private. By means of quantile regressions, we find that employer learning takes place at the low end of the income distribution as well as the upper end of the income distrib-

[6] Statistical tests available upon request.

ution. When differentiating between different type of occupation (blue collar vs. white collar) of different types of jobs (supervisory jobs or elementary jobs), we find no significant differences between groups. Finally, we check the sensitivity of our results to the choice of the research instrument by running the estimations with parents' educational attainment instead of literacy scores. Our results show that the choice of the measure of natural ability may drive the discrepancy between our results and those found in Germany as the alternative set of estimates is rather inconclusive. Our results suggest that the apprenticeship systems does not provide more accurate information on the true productivity of workers.

While our results suggest that employer learning takes place in Switzerland, alternative interpretations of our estimates could be put forward. Indeed, we performed statistical tests that could not rule out that alternative explanations of the dynamic pattern of the returns to education and literacy skills. While we indeed believe that employer learning is at work, further research is still needed to formally prove it.

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