Skill-persistence and the impact of post-compulsory education on skills – evidence from a linked PISA-PIAAC data set*

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Abstract: To what extent do the skills measured by the end of compulsory school persist in the adult ages and to what extend does post- compulsory education contribute to further skills of the adult population? These research questions are addressed in this paper. Students in the Programme for International Student Assessment (PISA) survey for year 2000 were re-interviewed in 2012 and asked to answer the tests and the questionnaire of the International Assessment of Adult Competencies (PIAAC). The preferred estimates are point estimates of the partial correlation coefficient between early and late literacy skills at 0.69 and that one more year of post-compulsory education results in an increase in literacy skills by 0.07 standard deviations. The estimate of persistence in skills is high and underscores the importance of compulsory school education providing skills as assessed in e.g. PISA.

Keywords: PISA, PIAAC, skills, measurement errors, instrumental variables

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1. Introduction

During recent years international assessments of the skills of school children have drawn considerable public interest, especially the results from the OECD Programme for International Student Assessment (PISA). Skills (or competencies) are generally viewed as an important element for success in the labour market and for other adult outcomes. Lasting effects of skills measured at the end of compulsory school would underline the importance of obtaining high levels of skills among school children as measured by PISA.

School reforms is one way to attempt to improve the skills of school children and there is evidence that some countries have adjusted curriculum standards to align with the competencies measured in PISA (see Heyneman and Lee (2017), p. 51-55). However, the impact of PISA on policy appears to vary substantially between countries, where Germany is an example of a large impact after being hit by "the PISA shock" (see Grek (2009) and Neumann et al. (2010)).

This paper addresses the following research questions. To what extent do the skills measured by the end of compulsory school persist in the adult ages and to what extend does post-compulsory schooling contribute to further skills of the adult population?

Answers to these questions are of importance for addressing the issue of the impact of the timing of investment in human capital. According to Heckman (2000), investment in human capital formation in the early stages of life has a higher pay off than investment in later stages of life.

Assessment of the skill of the adult population has been hampered by the lack of data that are comparable across countries. The release of the OECD Programme for the International Assessment of Adult Competencies (PIAAC) has made it possible to assess the skill level of the adult population in the participating countries. This survey was collected from 2011 to 2012, was released in the autumn of 2013 and covered a substantially number of countries (23 countries participated in the initial survey). Included in the survey that covers the population aged 16 to 65 is an assessment of skills and a background questionnaire.

The PIAAC survey makes it possible to analyse skills and outcomes on high quality data that are comparable across several countries. A link between the skills measured in PISA and the skills measured in PIAAC makes it possible to assess the impact of skills at the end of compulsory school on adult skills. As the PIAAC data includes information about the wage rates of the respondents, it furthermore becomes possible to assess the impact of skills at the end of compulsory school on adult wages. Hanushek et al. (2015) show substantial returns to skills as measured by PIAAC with respect to wage rates.

The aim of this paper is to answer the research questions by analysing a data set that contains skill measures from both PIAAC and from PISA. Students in the Danish PISA 2000 survey were re-interviewed in 2012 and asked to answer the tests and the questionnaire of the PIAAC. The PISA survey assessed young people's skills in reading, mathematics and science and the PIAAC survey assessed the skill level of the participants with respect to literacy, numeracy and problem solving. The respondents were aged 15, when they took the PISA test, and aged 27, when they were re-interviewed for the PIAAC survey. This paper analyses both the relationship between the PISA and the PIAAC literacy scores and the relationship between the PISA and the PIAAC numeracy scores. The analysis is conducted on high quality PISA and PIAAC data that are comparable across countries and the results of the paper are thus likely to have a high external validity.

Persistence in intelligence tests has been assessed in the previous literature. The survey by Neisser et al. (1996), p. 81, states that 'Intelligence test scores are fairly stable during development' and mention that Jones and Bayley (1941) found that scores obtained at age 18 had a correlation coefficient of 0.77 with scores obtained at age 6 and 0.89 with scores obtained at age 12.

A part of the literature has analysed both persistence and the impact of education on IQ. The survey by Winship and Korenman (1997), p. 221, contains six studies with measures of both education, early IQ and late IQ. The increase of an individual's IQ from one extra year of education varies in the studies from 1.0 points to 4.2 points according to the calculations presented in Winship and Korenman (1997), p. 221 (on the standard scale for measuring intelligence test, which has mean 100 and standard deviation 15). Two of the papers apply path analysis as methodology and obtain partial correlation coefficients between early and late IQ of 0.70 and 0.71 (see Wolfle (1980), p. 107 and Husén and Tuijnman (1991), p. 21).

Winship and Korenman (1997) furthermore reanalyse a subsample (of 1,253 participants) in the National Longitudinal Study of Youth (NLSY) used in Herrnstein and Murray (1994), which contains a measure of childhood cognitive ability. The outcome variable is the Armed Forces Qualifying Test (AFQT), taken in 1979 when the respondents were 14 to 20 years old. The result when both early IQ and the number of years of education (henceforth denoted schooling) enter the regression is a partial correlation coefficient of 0.36 between early IQ and the AFQT and that one extra year of education increases an individual's IQ by 2.7 points (Winship and Korenman (1997), p. 232).

Falch and Massih (2011) analyse the relation between IQ at age ten and an IQ test for enrolment in the military taken at age 20 for a sample of school children tested in 1938 in the Swedish city Malmö. The raw correlation between the early and the late test is 0.75, the partial correlation coefficient between late and early IQ attains value 0.53 in an OLS regression that also contains schooling, while the value becomes 0.65 in an IV regression, where both early IQ and schooling are instrumented (the coefficients on schooling are about 3.5 points, see Falch and Massih (2011), Table 4 and 5, sample sizes are 650 and 577).[1]

Most studies apply data that do not contain measures of both schooling, early IQ and late IQ. An example is Hansen et al. (2004), who also apply the NLSY (sample size 2,066) but condition on estimated latent ability in contrast to early IQ. The authors find that schooling increases the AFQT score on average between 2.8 and 4.2 points per additional year of education (Hansen et al. (2004), p. 79).

The data applied in this paper differ from the data used in the previous literature in several important ways. The previous literature analyses changes in IQ from about age ten to either 20 (the Malmö data) or to an IQ test taken when the respondents are between 14 to 20 years old (the NLSY). In contrast, this paper analyses changes in test performance from age 15 to age 27, implying both that the respondents are substantially older at the ages of both the early and the late test but also that the impact of schooling on test scores in this paper includes the effect of post-secondary schooling.

Moreover, the concept of intelligence and the interpretation of IQ tests is subject to an intense debate, where an influential school (represented by e.g. Herrnstein and Murray (1994)) emphasize the ability of IQ tests to measure ‘general intelligence’, denoted *g*. According to Ceci (1991), p. 705, this measure is supposed to be ‘a culture-free measure’ of the intellectual capacity of an individual that is ‘not susceptible to change as a function of schooling experience’.

The aim of the skills measures in PIAAC constructed by the OECD is close to the exact opposite. These skills are intended to measure “key information-processing competencies” that are relevant to adults in many social contexts and work situations. According to the OECD (2013), p. 28, the skills are “….‘learnable’. That is, countries can shape the level and distribution of these skills in their populations through the quality and equity of learning opportunities both in formal educational institutions and in the workplace.” With respect to the early skill measure, OECD (2003), p. 24, states analogously that ‘PISA provides international comparisons of the performance of education

[1] The study is a reanalysis of the data used in Husen and Tuijmman (1991), which is one of the studies included in the survey by Winship and Korenman (1997).

systems, with cross-culturally valid measures of competencies that are relevant to everyday adult life'.

Given the different aims of intelligence tests and the skill measures by the OECD, it is questionable a priory to what extent results from IQ tests with respect to persistence and returns to schooling are valid for skill measures. Three previous studies have addressed the research questions of this paper with respect to skill measures. The contribution by Gustafsson (2016) indicates that skills at age 15, as measured by the PISA surveys, have a significant impact on adult skills, as measured by the PIAAC surveys. Lasting effects of skills obtained in compulsory education are also found in Rosdahl (2014), who finds a high correlation between the PISA literacy level at age 15 and the PIAAC literacy level at age 27 on the data set applied in this paper. Albæk and Rosdahl (2017) find that younger Finns tend to have higher PIAAC numeracy skills than Scandinavians (consistent with the results from PISA), while older Finns have lower numeracy skills than Scandinavians (consistent with the later implementation in Finland of the Nordic national educational reforms that increased the quality and quantity of education).

A core element of the present paper is that it addresses the question of the extent to which analyses on the PIAAC data yields reliable estimates. Estimators might be biased as a consequence of endogeniety of the PISA skill measure and schooling, including the presence of measurement errors, and the paper applies instrumental variable estimation in an attempt to obtain consistent estimates. The impact of measurement errors in both skills and schooling on the parameter estimates appears to be large. This paper develops and applies a methodology that enables an assessment of the magnitude of the biases that occur in the estimates, if the estimating procedure does not fully account for measurement errors in both skills and schooling.

The remainder of the paper is organized as follows. Section 2 presents the methodology of the paper. Section 3 introduces the PISA and the PIAAC data. Section 4 presents bivariate and multivariate analyses. Section 5 contains the instrumental variable analysis. Section 6 performs robustness checks. Section 7 discusses the results. Section 8 concludes.

2. Methodology

This section presents the methodological framework for the analyses in the paper. First the empirical model is presented, followed by the expected results of the estimating procedures, which are applied in the empirical sections.

These sections show that the core variables applied in the analyses are measured with errors and that these measurement errors have implications not only for the parameter estimates but also for the inferences that can be drawn from these estimates. This section shows how the parameter estimates of the procedures applied in the paper are affected by measurement errors in the variables. Differences in parameter estimates between the procedures can partly be ascribed to differences in the effects of measurement errors. The procedures are bivariate regression, multivariate analysis and instrumental variable regressions.

The paper investigates outcome y, the late skill level of the respondent, described by the equation

$$y = \gamma x + \beta S + u, \tag{1}$$

where x is the early skill level and S is the number of years of education. The variables are measured as deviations from their means. The parameters to be estimated are γ and β, while u is the error term. The late skill level, y, and the number of years of education, S, is measured in PIAAC at age 27, while the early skill level, x, is measured in PISA at age 15.

Parameter γ measures the impact of the early skill on the late skill level and is thus a measure of persistence in skills. A large γ indicates a high degree of persistence in skills from compulsory school to skills at age 27.

Parameter β measures the impact of the number of years of education on skills at age 27. At the time of the PISA test the respondents had the same number of years of education as they still attended compulsory education, and differences in variable S between the respondents is thus due to differences in school attendance beyond compulsory education. Schooling beyond compulsory education is an investment whose returns can be assessed in terms of increased skills or in terms of for example increased wage rates. A large β indicates a high effect of post-compulsory education on the skill level at age 27, that is, a large return to schooling.

The expected signs are thus β>0 and γ>0, which is assumed in the following unless otherwise stated. It is also assumed that there is a positive association between skills in compulsory school and schooling, that is, covariance $\sigma_{Sx} > 0$, which is an empirical regularity that is also found in the data for this paper.

The actual early skill level, x, is not observed, but a test, $\tilde{x}$, is observed, such that the relation between the actual and the measured skill level is written as

$$\tilde{x} = x + \epsilon, \tag{2}$$

where ϵ is the measurement error, which has variance σ_ϵ^2. The measurement errors are assumed to follow the classical assumptions, that is, zero correlation between measurement errors and the unobserved skill level, $\sigma_{x\epsilon} = 0$, implying $\sigma_{\tilde{x}}^2 = \sigma_x^2 + \sigma_\epsilon^2$ and $\sigma_{\epsilon\tilde{x}} = \sigma_\epsilon^2$. Furthermore, the measurement errors are not correlated with the error term and other explanatory variable in the regression equation (1), $\sigma_{u\epsilon} = \sigma_{S\epsilon} = 0$.

Correspondingly, the actual schooling level, S, is not observed such that the observed schooling level, $\tilde{S}$, equals

$$\tilde{S} = S + \upsilon, \tag{3}$$

where υ is the measurement error that fulfils $\sigma_{x\upsilon} = \sigma_{u\upsilon} = 0$, and $\sigma_{S\upsilon} = 0$, implying $\sigma_{\tilde{S}}^2 = \sigma_S^2 + \sigma_\upsilon^2$ and $\sigma_{\upsilon\tilde{S}} = \sigma_\upsilon^2$.

Insertion of equation (2) and (3) into (1) yields the empirical model

$$y = \gamma\tilde{x} + \beta\tilde{S} + (u - \gamma\epsilon - \beta\upsilon). \tag{4}$$

In the deductions in this section the standard regression assumptions $\sigma_{xu} = \sigma_{Su} = 0$ are assumed to be fulfilled.

The next sections of the paper present the results of different procedures for obtaining the parameters of the estimating equation (4). The analytical solutions for the parameter estimates in the different cases are as follows.

Consider first the estimate of skill persistence in the bivariate regression of y on skill measure $\tilde{x}$, omitting the schooling variable $\tilde{S}$. The bias of the estimate $\hat{\gamma}^B$ becomes

$$plim\ \hat{\gamma}^B - \gamma = \alpha_{\tilde{S}\tilde{x}}\beta - \lambda_{\tilde{x}}\gamma, \tag{5}$$

where $\alpha_{\tilde{S}\tilde{x}} = \sigma_{\tilde{S}\tilde{x}}/\sigma_{\tilde{x}}^2$ is the coefficient in the regression of $\tilde{S}$ on $\tilde{x}$ and $\lambda_{\tilde{x}} = \sigma_\epsilon^2/\sigma_{\tilde{x}}^2$ is a measure of the relative amount of measurement error in the observed skill measure $\tilde{x}$. The first term on the right hand side is the omitted variable bias, which is positive (given the assumptions β>0 and $\sigma_{\tilde{S}\tilde{x}} >$

0). The second term on the right hand side is the measurement error bias, which is negative (given γ>0). The sign of the bias of the persistence in skills in the bivariate regression is thus indeterminate. The regression coefficient overestimates skill persistence if the omitted variable bias is large relative to the bias stemming from the measurement errors in the skill variable and underestimate skill persistence if the omitted variable bias is small relative to the measurement error bias.[2]

Then consider the corresponding estimate of returns to schooling in a bivariate regression of y on $\tilde{S}$, omitting the skill measure $\tilde{x}$. The bias of $\hat{\beta}^B$ becomes

$$plim\ \hat{\beta}^B - \beta = \alpha_{\tilde{x}\tilde{S}}\gamma - \lambda_{\tilde{S}}\beta, \tag{6}$$

where $\alpha_{\tilde{x}\tilde{S}} = \sigma_{\tilde{S}\tilde{x}}/\sigma_{\tilde{S}}^2$ is the coefficient in the regression of $\tilde{x}$ on $\tilde{S}$ and $\lambda_{\tilde{S}} = \sigma_v^2/\sigma_{\tilde{S}}^2$ is a measure of the relative amount of measurement error in the observed schooling measure $\tilde{S}$. The first term on the right hand side is the omitted variable bias, which is positive. The second term on the right hand side is the measurement error bias, which is negative.

In the multivariate regression, where both $\tilde{S}$ and $\tilde{x}$ are included as regressors, calculations yield that the bias of the estimator of skill persistence, $\hat{\gamma}^M$, becomes

$$plim\ \hat{\gamma}^M - \gamma = \frac{\alpha_{\tilde{S}\tilde{x}}\lambda_{\tilde{S}}}{1-\rho^2}\beta - \frac{\lambda_{\tilde{x}}}{1-\rho^2}\gamma, \tag{7}$$

where $\rho = \sigma_{\tilde{S}\tilde{x}}/\sigma_{\tilde{S}}\sigma_{\tilde{x}}$ is the correlation coefficient between $\tilde{x}$ and $\tilde{S}$. The first term on the right hand side of (7) is positive and due to the measurement errors in the schooling variable. The second term is negative and due to the measurement errors in the skill variable. The sign of the bias of $\hat{\gamma}^M$ is indeterminate.

The relative magnitude of the four terms in the expressions for the biases of $\hat{\gamma}^M$ and $\hat{\gamma}^B$ is assessed as follows. The second term on the right hand side of equation (7) is larger in absolute value than the second term on the right hand side of equation (5) (as $0 < \rho < 1$). The bias stemming from the measurement errors in the skill measure is thus larger in absolute value in the multivariate regression than in the bivariate regression. The first term on the right hand side of equation (7) is smaller than first term on the right hand side of equation (5) (as the ratio $\lambda_{\tilde{S}}/(1-\rho)$ is less than

[2] In the special cases of $\beta = 0$ or $\sigma_{\tilde{S}\tilde{x}} = 0$, that is, no omitted variable bias, equation (5) becomes $plim\ \hat{\gamma} = (1-\lambda_{\tilde{x}})\gamma$, where $1-\lambda_{\tilde{x}} = \sigma_x^2/(\sigma_x^2+\sigma_\epsilon^2)$ is the 'reliability ratio' of $\tilde{x}$.

one).[3] The bias stemming from the measurement error bias in the schooling variable in the multivariate regression is thus smaller than the bias stemming from omitting the schooling variable in the bivariate regression.

It follows that the bias in skill persistence in the multivariate equation is numerically smaller than the bias in the univariate equation, which is confirmed by calculations on the terms in the difference between equations (5) and (7):

$$plim\,\hat{\gamma}^M - plim\,\hat{\gamma}^B = -\alpha_{\tilde{S}\tilde{x}} \frac{\sigma_S^2(1-\rho^2)}{\sigma_v^2 + \sigma_S^2(1-\rho^2)}\beta - \frac{\lambda_{\tilde{x}}\rho^2}{1-\rho^2}\gamma < 0. \tag{8}$$

It is possible to select $\hat{\gamma}^M$ as an estimate preferred to $\hat{\gamma}^B$ in the case where there are no measurement errors in the skill variable, $\sigma_\epsilon^2 = 0$. In this case the biases of both $\hat{\gamma}^B$ and $\hat{\gamma}^M$ are positive, but the bias of $\hat{\gamma}^M$ is smaller than the bias of $\hat{\gamma}^B$ (as the second terms in (5), (7) and (8) vanish). Inclusion of a variable with measurement errors (in this case the schooling variable) in the estimating equation thus results in a smaller bias than omitting this variable, which is the main result in McCallum (1972).

However, if measurement errors are also present in the skill variable, $\sigma_\epsilon^2 > 0$, the sign of the biases in neither the bivariate nor the multivariate regression are known. In the case of a negative bias in the bivariate regression, $plim\,\hat{\gamma}^B - \gamma < 0$, the absolute value of the bias becomes with certainty larger in the multivariate regression than in the bivariate regression. The result in McCallum (1972) – that inclusion of a variable affected by measurement errors is always preferable to the bivariate regression – does thus not extend to the case where the regressor in the bivariate regression is affected by measurement errors.

The corresponding estimate of the returns to schooling in the multivariate regression becomes

$$plim\,\hat{\beta}^M - \beta = \frac{\alpha_{\tilde{x}\tilde{S}}\lambda_{\tilde{x}}}{1-\rho^2}\gamma - \frac{\lambda_{\tilde{S}}}{1-\rho^2}\beta. \tag{9}$$

The first term on the right hand side is positive and due to the measurement errors in the skill variable. The second term is negative and due to the measurement errors in the schooling variable. The sign of the bias of $\hat{\beta}^M$ is indeterminate.[4]

[3] The ratio can be rewritten as $\sigma_v^2/\left(\sigma_v^2 + \sigma_S(1-\rho_{S\tilde{x}})\right)$, where $\rho_{S\tilde{x}} = \sigma_{S\tilde{x}}/\sigma_S\sigma_{\tilde{x}}$ is the correlation coefficient between $\tilde{x}$ and S.

The difference between the estimates of returns to schooling in the multivariate and the bivariate regressions becomes

$$plim\,\hat{\beta}^M - plim\,\hat{\beta}^B = -\alpha_{\tilde{x}\tilde{S}} \frac{\sigma_\epsilon^2\left(1-\rho_{\tilde{S}x}^2\right)}{\sigma_\epsilon^2+\sigma_x^2\left(1-\rho_{\tilde{S}x}^2\right)}\gamma - \frac{\lambda_{\tilde{S}}\rho^2}{1-\rho^2}\beta < 0, \tag{10}$$

where $\rho_{\tilde{S}x} = \sigma_{\tilde{S}x}/\sigma_{\tilde{S}}\sigma_x$ is the correlation coefficient between $\tilde{S}$ and x. The estimate of the returns to schooling is numerically smaller in the multivariate regression than in the bivariate regression.

The biases of the parameters in the multivariate regressions are connected. In the special case of no measurement errors in the skill variable, $\sigma_\epsilon^2 = 0$, combining equations (7) and (9) yields

$$plim\,\hat{\gamma}^M - \gamma = -\alpha_{\tilde{S}\tilde{x}}\left(plim\,\hat{\beta}^M - \beta\right). \tag{11}$$

A downward bias in the estimate of the returns to schooling $\left(plim\,\hat{\beta}^M - \beta < 0\right)$ as a consequence of measurement errors in schooling thus translates into an upward bias in persistence $(plim\ \hat{\gamma}^M - \gamma > 0)$. The magnitude of the upward bias in persistence is large when the coefficient in the auxiliary regression of schooling on early skills, $\alpha_{\tilde{S}\tilde{x}}$, is high.

In the analogous case of no measurement errors in the schooling variable, $\sigma_v^2 = 0$, the relation between the biases becomes

$$plim\,\hat{\beta}^M - \beta = -\alpha_{\tilde{x}\tilde{S}}(plim\,\hat{\gamma}^M - \gamma), \tag{12}$$

A downward bias in the estimate of persistence $(plim\,\hat{\gamma}^M - \gamma < 0)$ as a consequence of measurement errors in the skill variable thus translates into an upward bias in the returns to schooling $\left(plim\,\hat{\beta}^M - \beta > 0\right)$. The magnitude of the upward bias in the returns to schooling is large when the coefficient in the auxiliary regression of early skills on schooling, $\alpha_{\tilde{x}\tilde{S}}$, is high.

A remedy to remove the impact of measurement errors on the parameter estimates is to apply instrumental variable regression. Consider first the consequences of instrumenting the skill variable. The first stage equation in a two stage least square (2SLS) procedure is

[4] Specialized or abbreviated versions of equations (7) and (9) are contained in Griliches (1986), p. 1479 and Bound et al. (2001), p. 3716.

$$\tilde{x} = a_1 z_1 + a_2 \tilde{S} + \zeta_1. \tag{13}$$

The predicted values from this equation, $\hat{x}$, are used as regressor in the second stage regression

$$y = \gamma \hat{x} + \beta \tilde{S} + (u - \gamma \epsilon - \beta v). \tag{14}$$

The assumptions are $cov(z_1, x) > 0$ and $cov(z_1, u - \gamma\epsilon - \beta v) = 0$.

The biases in the 2SLS estimate become

$$plim\, \hat{\gamma}_x^{IV} - \gamma = \frac{\alpha_{\tilde{S}\hat{x}} \lambda_{\tilde{S}}}{1 - \rho_{\tilde{S}\hat{x}}^2} \beta > 0, \tag{15}$$

and

$$plim\, \hat{\beta}_x^{IV} - \beta = -\frac{\lambda_{\tilde{S}}}{1 - \rho_{\tilde{S}\hat{x}}^2} \beta < 0. \tag{16}$$

where $\alpha_{\tilde{S}\hat{x}}$ is the coefficient in the regression of $\tilde{S}$ on $\hat{x}$ and $\rho_{\tilde{S}\hat{x}}$ is the correlation coefficient between $\tilde{S}$ and $\hat{x}$.

The 2SLS procedure with instruments for the skill variable removes the inconsistency of the skill parameter estimate caused by the measurement errors in the skill variable, but the inconsistency caused by measurement errors in the schooling variable remains. Given the validity of the instruments, $\hat{\gamma}_x^{IV}$ is thus an upper bound for persistence in skills and $\hat{\beta}_x^{IV}$ is a lower bound for the effect of schooling on skills.

The expression for $\hat{\gamma}_x^{IV}$ is similar to the expression for $\hat{\gamma}^M$ in equation (7) omitting the second term on the right hand side that captures the effect of measurement errors in the skill variable, and the expression for $\hat{\beta}_x^{IV}$ is similar to the one for $\hat{\beta}^M$ in equation (9) omitting the first term on the right hand side that expresses the effect of measurement errors in the skill variable on the returns to schooling. The magnitude of the biases in the estimates of $\hat{\gamma}_x^{IV}$and $\hat{\beta}_x^{IV}$ are connected in the same way as the biases of $\hat{\gamma}^M$ and $\hat{\beta}^M$ are connected in equation (11), which is obtained under the assumption of no measurement errors in the skill variable.

Consider next the consequences of instrumenting the schooling variable. The first stage equation in a two stage least square procedure implies that $\tilde{S}$ enter on the left hand side in the place of $\tilde{x}$

in a regression analogous to (13) while $\tilde{x}$ enters on the right hand side. The second stage implies that $\hat{S}$ and $\tilde{x}$ enter in the place of $\tilde{S}$ and $\hat{x}$ on the right hand side in an regression analogous to (14).

The biases become

$$plim\,\hat{\gamma}_S^{IV} - \gamma = -\frac{\lambda_{\tilde{x}}}{1-\rho_{\hat{S}\tilde{x}}^2}\gamma < 0, \tag{17}$$

and

$$plim\,\hat{\beta}_S^{IV} - \beta = \frac{\alpha_{\tilde{x}\hat{S}}\lambda_{\tilde{x}}}{1-\rho_{\hat{S}\tilde{x}}^2}\gamma > 0. \tag{18}$$

where $\alpha_{\tilde{x}\hat{S}}$ is the coefficient in the regression of $\tilde{x}$ on $\hat{S}$ and $\rho_{\hat{S}\tilde{x}}$ is the correlation coefficient between $\hat{S}$ and $\tilde{x}$.

The 2SLS procedure with instruments for the schooling variable removes the inconsistency of parameter estimates caused by the measurement errors in this variable, but the inconsistency caused by the measurement errors in the skill variable remains. Given the validity of the instruments, $\hat{\gamma}_S^{IV}$ is thus a lower bound for persistence in skills and $\hat{\beta}_S^{IV}$ is an upper bound for the returns to schooling.

The expression for $\hat{\gamma}_S^{IV}$ corresponds to the second term on the right hand side in the expression for $\hat{\gamma}^M$ in equation (7) and the expression for $\hat{\beta}_S^{IV}$corresponds to the first term on the right hand side in the expression for $\hat{\beta}^M$ in equation (9). The biases from the estimates $\hat{\gamma}_S^{IV}$ and $\hat{\beta}_S^{IV}$ are connected analogously to the connection between biases for $\hat{\gamma}^M$ and $\hat{\beta}^M$ under the assumption of no measurement errors in the schooling variable, se equation (12).

Finally consider the 2SLS procedure in the case where both the skill variable and the schooling variable are instrumented. This procedure yields consistent estimates of both γ and β that are denoted by $\hat{\gamma}_{xS}^{IV}$ and $\hat{\beta}_{xS}^{IV}$.

Measurement errors in the skill variable in a multivariate regression result in biases in both the coefficient on the skill variable and in the coefficient on the schooling variable, and measurement errors in the schooling variable also result in biases in the coefficients on both the schooling and the skill variable. The magnitude of these four components of the biases of the coefficients in the multivariate equation can be estimated as follows.

The bias in skill persistence caused by measurement errors in the schooling variable appears on the right hand side of equation (15) that states the expression for the bias in $\hat{\gamma}_x^{IV}$. This bias can be estimated by the difference in parameter estimates $\hat{\gamma}_x^{IV} - \hat{\gamma}_{xS}^{IV}$, as $\hat{\gamma}_{xS}^{IV}$ is a consistent estimate of γ. Another expression of the bias appears as the first term on the right hand side of equation (7) that states the expression for the bias in $\hat{\gamma}^M$. The bias in skill persistence caused by measurement errors in the skill measure appears both as the second term in equation (7) and on the right hand side of equation (17), the expression for the bias in $\hat{\gamma}_S^{IV}$. The difference $\hat{\gamma}^M - \hat{\gamma}_S^{IV}$ is thus another estimate of the upward bias in skill persistence caused by measurement errors in the schooling variable.

Estimates of the magnitude of the other three components of the biases are obtained analogously. The magnitude of the downward bias in the returns from schooling stemming from measurement errors in the schooling variable is estimated by $\hat{\beta}_x^{IV} - \hat{\beta}_{xS}^{IV}$ and $\hat{\beta}^M - \hat{\beta}_S^{IV}$. The downward bias in skill persistence stemming from measurement errors in skills is estimated by $\hat{\beta}_x^{IV} - \hat{\beta}_{xS}^{IV}$ and $\hat{\gamma}^M - \hat{\gamma}_x^{IV}$, and the upward bias in returns to schooling stemming from measurement errors in skills is estimated by $\hat{\beta}_S^{IV} - \hat{\beta}_{xS}^{IV}$ and $\hat{\beta}^M - \hat{\beta}_x^{IV}$.

The components in the biases of the parameter estimates in the bivariate regressions can be recovered as follows. The downward bias in skill persistence is estimated as $\lambda_{\tilde{x}}\gamma = \left(1 - \hat{\rho}_{\tilde{S}\tilde{x}}^2\right)\left(\hat{\beta}_S^{IV} - \hat{\beta}_{xS}^{IV}\right)$ while the downward bias in returns to schooling is estimated as $\lambda_{\tilde{S}}\beta = \left(1 - \hat{\rho}_{\tilde{S}\hat{x}}^2\right)\left(\hat{\beta}_x^{IV} - \hat{\beta}_{xS}^{IV}\right)$. The upward bias in skill persistence due to omission of the schooling variable is estimated as $\hat{\alpha}_{\tilde{S}\tilde{x}}\hat{\beta}_{xS}^{IV}$ while the upward bias in returns to schooling due to omission of the skill variable is estimated as $\hat{\alpha}_{\tilde{S}\tilde{x}}\hat{\gamma}_{xS}^{IV}$

Section four of the paper reports estimates for the bivariate and multivariate regressions. Section five reports estimates using instrumental variable analysis and includes an assessment of the magnitude of the various biases in the multivariate and the bivariate regressions.

3. The data

This section describes the data for the paper, which is a combination of two data sets collected by the OECD. The point of departure is the students who participated in PISA in year 2000. These students were re-interviewed in 2012 and asked to answer the tests and the questionnaire of PIAAC. First the content of the PISA data is described, followed by the PIAAC data, and then the content of the combined data set is described more closely.

The PISA survey assesses young people's literacy in reading, mathematics and science. The aim is to assess young people's capacity to use knowledge and skills in order to meet real-life challenges (see OECD (2002)). The PISA 2000 survey was a paper-and-pencil test taken at schools. In addition to the assessments, PISA 2000 included student and school questionnaires.

The PIAAC survey of adult skills assesses the proficiency of adults aged 16-65 for three measures of cognitive skills: literacy, numeracy, and problem-solving. These skills are intended to measure ‘key information-processing competencies’ that are relevant to adults in many social contexts and work situations.

Representative samples of the adult population were interviewed in their homes in the language of their country.[5] While questions were answered via computer, respondents with no computer experience could use paper and pencil. The interview included both a background questionnaire and questions for the assessment of cognitive skills.

According to the OECD (2013), the assessment domains in PIAAC are as follows. *Literacy* is the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one’s goals, and to develop one’s knowledge and potential. *Numeracy* is the ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life. *Problem-solving* is the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks. This paper focuses on literacy and numeracy.

The point of departure for formation of the data set used in this paper is 4,235 Danes, who were born in 1984 and participated in PISA 2000. These persons were re-interviewed and asked to answer the PIAAC tests and the questionnaire in 2012. However, we were only able to obtain PIAAC information for 1,881 out of the 4,235 PISA participants. The main reasons for this attrition are a) ‘protection against researchers’, meaning that researchers are not allowed to contact the respondents (1,074 participants), b) that the respondents did not wish to participate (526 participants), c) unknown personal identification number (308 respondents), d) unknown address – cannot be contacted (277 participants), e) dead, immigrated, or institutionalised (119 respondents), and f) sickness, handicap, reading- or writing problems (50 participants). Furthermore, one observation was dropped because of lack of information about the number of years of education.

The 1,880 respondents in the combined data set is the starting point for the analysis of this paper. PISA 2000 focused on reading skills as the main domain and the mathematics test was only administered to a subsample of 1,055 of the participants. Separate analyses are carried out for reading on the whole sample and mathematics for the subsample.

[5] The data for the first wave was collected for 24 participating countries: Austria, Belgium (only Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland) and the United States.

The PISA 2000 data contains sampling weights to align the respondents with the population of persons aged 15 in year 2000. Statistics Denmark recalculated the sampling weights to align the respondents in the PISA-PIAAC data to the population. These sampling weights are applied throughout the analyses. The analyses in this paper involve the following variables from the data set: the PISA 2000 supplies scores for reading skills and mathematics skills and PIAAC also supplies literacy scores and the numeracy scores.

Table 1 presents descriptive statistics for the variables in the analyses and contains the mean values and the standard deviations for the variables. The average PISA literacy score for the sample is 497.4 and the standard deviation is 97.2, which is close to the average for all participating countries, as the OECD constructs the scale for the PISA score with a mean score of 500 and a standard deviation of 100 among the 32 participating OECD countries (OECD (2002), p. 35). The average PISA numeracy score is 515.4 and thus higher than the OECD average, and the standard deviation of 84.9 is lower.

Table 1 around here

The mean PIAAC score for literacy of 293.7 is larger than the mean literacy proficiency of 270.1 among 16-65 year-old Danes (OECD (2013), p. 259), and the same is the case for the numeracy score of 297.6, which is larger than the mean numeracy proficiency of 278.3 (OECD (2013; 2013), p. 266). The respondents in the PISA-PIAAC data have average scores that are larger than the average among 16-65 year-old Danes as the age category 25-34 have larger scores than both younger and older respondents (OECD (2013), p. 107). As proficiency varies with age, the standard deviations in the PISA-PIAAC data (35.4 for literacy and 41.9 for numeracy) are smaller than the standard deviations among 16-65 year-olds Danes (49.0 for literacy and 51.2 for numeracy, see OECD (2013), p. 259 and p. 266).[6]

The marks of the students from PISA also enter the analyses. The information on the marks of the students is based on the student questionnaire, OECD (2000b), the first part of question number 41 (Q41): ‘In your last school report, what mark did you receive in the following subjects?’, where the subjects are language, mathematics and science. Furthermore, as the second part of Q41, the questionnaire asks the students ‘In your last school report, how did your mark compare with the

[6] The paper uses the plausible value that is closest to the average of the plausible values. The literacy analysis uses plausible value three in the PISA literacy data and value five in the PIAAC literacy data, while the numeracy analysis uses plausible value five in the PISA numeracy data and value two in the PIAAC numeracy data.

pass mark in each subject area' with the following answer categories: 'above the pass mark', 'at the pass mark' and 'below the pass mark'.

The marks in the Danish PISA data falls in ten distinct numerical categories on a scale with a minimum score of zero and a maximum score of 100 (the remaining categories are 23, 38, 46, 54, 62, 69, 77 and 85).[7] In year 2000 the Danish grading scale also had ten categories with a minimum score of zero and a maximum of 13, and with a pass mark of six (the scale contained marks numbered 0, 3, 5, 6, 7, 8, 9, 10, 11 and 13). Cross tabulations of the first and the second part of Q41 yield the result that all students 'at the pass mark' have a score of 46 on the zero-to-100-scale (mark number four on the scale), all students with higher scores have marks 'above the pass mark', and all students with lower scores have marks 'below the pass mark'. These findings are thus consistent with a mapping of the marks from the Danish grading scale into a scale ranging from zero to 100, where the pass mark is mapped from six to 46. The distribution of marks in categories on the zero-to-100-scale has the shape of a typical distribution of primary school marks on the Danish grading scale from zero to 13.

Table 1 shows that the average marks in reading and math for students with marks in the data are slightly higher than the average marks in science. Marks are missing in reading, mathematics and science for seven, seven and 12 per cent of the students, respectively. Missing values enter in the regressions as dummy variables, which take value one for a missing observation and zero otherwise. Table 1 also shows that the data contain 50 per cent females and 5 per cent respondents, where both parents were both born abroad.

The PIAAC data furthermore contain variables constructed from parental education categorised according to three levels of education according to the International Standard Classification of Education (ISCED): a low educational category (ISCED 1, 2 and 3C short), a middle educational category (ISCED 3 except 3C short), and a high educational category (ISCED 5 and 6). This information on parental education exists for both the mother and the father. Parental education enters as a variable that takes value -1 if the parent belongs to the low educational category, 0 if the parent belongs to the middle educational category, and +1 if the parent belongs to the high educational category.

The family background in PIAAC includes a variable for the father being absent, which was the case for 18.5 per cent of the respondents. PIAAC contains a variable indicating the number of books at home at childhood. This variable is transformed from a categorical variable to a continuous

[7] The OECD (2000a), p. 130, states that the participating countries submitted data for the first part of Q41 in different formats, where one of the formats is a scale with a maximum score of 100.

one, which has mean 230 and standard deviation 237 books. The quarter of birth in the year is also included in the data.

The paper also applies the results from the PISA survey that indicates how happy the children are with the school. The question is ST31Q07, ‘My school is a place where I do not want to go’ with the following answer categories: strongly disagree, disagree, agree, and strongly agree. In the data these categories are assigned value 1, 2, 3 and 4, respectively, and Table 1 shows that the average response takes value 1.85.

The level of education is measured as the number of years of education at age 27. The paper applies two measures. The first is a PIAAC variable that is derived from the respondent’s answers to a question about the highest obtained education. Each country participating in PIAAC converts the answers on this question into a variable for the number of years of education. The average of this variable is 13.22 years and the standard deviation of the variable is 2.28. The second variable indicating the number of years of education stems from Danish registers at Statistics Denmark, who has merged the PISA-PIAAC data with Danish register data. Statistics Denmark receives information from each educational institution about the persons that complete every single educational programme in Denmark. For each single educational program in Denmark, the Danish Ministry of Education determines the duration of the education if the students pass the examinations according to the schedule, and this number is used for funding educational institution. Statistics Denmark applies these numbers to obtain a number of the years of education for each completed student, as measured by students who completed educations according to the schedule. This register schooling measure has an average of 14.50 years and a standard deviation of 2.38.

The mean age was 15.7 when the participants took the PISA test and 27.0 when they took the PIAAC test. The dispersion in age is very limited. The exposition denotes the participants as having age 15, when they took the PISA test, and age 27, when they took the PIAAC test.

The test score variables that enter the analyses are normalized by subtracting the means and divide by the standard deviations that appear in Table 1. The same is done for the variable for the number of books during childhood and the variable for not wanting to go to school.

4. Bivariate and multivariate analyses

This section analyses the relation between the skill measures in PIAAC at age 27 and the skills measures in PISA at age 15. At the centre of the analysis is the issue of the extent to which the PI-

SA scores at age 15 are able to predict the PIAAC scores at age 27 and to what extent post-compulsory education has an impact on measured skills at age 27.

Table 2, Panel A shows the results of regressions of the PIAAC literacy scores on the PISA literacy scores and the number of years of education as measured by PIAAC. Column 1 in Table 2 shows that a regression of the PIAAC literacy scores on PISA literacy yields an estimate of 0.56 implying that an increase in the PISA score of one standard deviation increases the PIAAC score by 0.56 standard deviations. As both the PIAAC and the PISA scores are normalized to have standard deviation one, the estimate is a correlation coefficient (and the value of the R-square statistics of 0.31 is thus the square of the regression coefficient). The regression coefficient suffers from an upward bias stemming from the omission of the schooling variable and from a downward bias stemming from measurement errors in the PISA scores (according to equation (5) in the methodology section).

Table 2 around here

Column 2 shows that one more year of education increases the PIAAC numeracy scores of 0.17 standard deviations according to the estimate of returns to schooling in a bivariate regression. This bivariate estimate is upward biased as the skill measure is omitted and downward biased as a consequence of measurement errors in the schooling variable (according to equation (6)).

Column 3 shows the result when both the PISA score and schooling enter as explanatory variables. The estimate on the PISA score decreases from 0.56 in column 1 to 0.48 in column 3 (in accordance with the expression stated in equation (8)). This estimate is biased downwards as a consequence of measurement errors in the skill variable and upwards as a consequence of measurement errors in the schooling variable (equation (7)). The returns to schooling decreases from 0.17 in column 1 to 0.07 in column 3 (in accordance with equation (10)). This estimate is biased downwards as a consequence of measurement errors in the schooling variable and upwards as a consequence of measurement errors in the skill variable (equation (9)).

Column 4 in Table 2 shows that females have slightly lower PIAAC literacy scores than males amounting to 0.07 standard deviations. However, when the female dummy enters together with the PISA literacy score in column 5, the differential increases to 0.30 standard deviations, and girls have thus higher scores than boys in the PISA literacy test.[8] The coefficients on early literacy skills and schooling in column 5 are nearly the same as the coefficients in the multivariate regression without the female dummy in column 3.

Table 2, Panel B shows the analogous results when PIAAC numeracy enter as the dependent variable and PISA numeracy enter as an explanatory variable. With one exception there are no significant differences between the coefficients for literacy in Panel A and the coefficients for numeracy in Panel B. The exception is the coefficient on the female dummy, which shows that females have 0.40 standard deviations lower PIAAC numeracy scores than males. The coefficient in column 5 where PISA numeracy and schooling also enter is almost the same, which indicates that girls-boys differences in PISA numeracy is small.

5. Instrumental variable analysis

The previous section presented OLS estimates of skill persistence and returns to education. This section presents the results from instrumental variable regressions, which has the potential of removing the impact of the measurement errors in early skills and schooling. The section first presents the first stage regressions in the two stage least square procedure and then the second stage regressions.

The first column in Table 3 shows the result of a first stage regression for the PISA scores when marks from compulsory school enter as instruments. An increase of one standard deviation in language (Danish) marks results in an increase of 0.33 standard deviations in the PISA reading score, while a one standard deviation increase in mathematics and the science marks increase the PISA reading score by 0.23 and 0.18 standard deviations, respectively. Conditional on marks, girls have 0.20 standard deviations higher scores in the PISA test than boys.

Table 3 around here

The second column shows the result for other instrumental variables than marks. An increase in the educational background of the mother from either the lowest to the middle or from the middle

[8] According to Solheim and Lundetræ (2016), one reason girls do better in PISA than boys might be that the assessment in PISA is more 'girl-friendly' in the sense that PISA contains a relatively high share of items that girls typically are better to answer than boys (e.g. fiction texts in contrast to non-fiction texts).

to the top educational category is associated with an increase in the PISA reading score by 0.20. The similar result for the educational background of the father is 0.15 standard deviations. An immigrant background reduces the PISA reading score by 0.43 standard deviations. An increase in the number of books at home by one standard deviation is associated with an increase in the PISA score of 0.14 standard deviations.

The third column shows the results when both the marks from column 1 and the variables from column 2 enter the regression. The coefficients of the marks diminish slightly when parental and other variables enter the regression equation but the reductions from the results in column 1 are not significantly different from zero. In contrast, the coefficients on parental educational background and books are reduced to about half of the size of the coefficients in column 2 when marks are added to the regression.

Column 4 supplements the variables in column 3 with the schooling variable from register information. Most of the coefficients in column 4 are slightly lower than the ones in column 3 but the differences are not significant.

Columns 5 to 7 show analogous results for the first stage regressions when the schooling variable is instrumented. Column 5 contains the same set of variables as column 3 and shows that females attains 0.46 years more education than males, conditional on the other explanatory variables. One standard deviation increase in language marks is associated with 0.47 more years of post-compulsory education, while the results for mathematics and science marks are 0.23 and 0.39 years, respectively. A higher educational level of both the mother and the father is associated with longer education of the child and more books at home are also associated with longer education. The child gets 0.44 years less post-compulsory education if the father is absent from the home, and an increase in the variable ‘Do not want school’ corresponding to one standard deviation is associated with 0.14 less number of years of schooling. Both the absence of the father and happiness with the school has thus consequences for the amount of post-compulsory schooling but has no impact on the PISA score according to the results in column 3.

In column 6 the schooling variable from the survey is regressed on the schooling variable from the registers and the female dummy, while the remaining variables from 5 also enter the regression in column 7. The inclusion of the schooling variable from the Danish registers implies that most of the coefficients in column 7 are lower than the corresponding estimates in column 5. Two of the quarter-of-birth dummies are significant in column 7.

The instruments include marks from primary school and the register schooling variable that are alternative observations for ability and schooling. Also included as instruments are quarter of birth, which is applied in Angrist and Krueger (1991) on a large data set and in for example Neal and Johnson (1996) and Hansen et al. (2004) on data sets of the same magnitude as the one applied for this paper. Most of the other variables are family background variables that after the introduction in Griliches and Mason (1972) are standard instruments for correcting for the effects of endogeneity of ability and schooling. An exception is the variable for how happy the child is going to school, which is a novelty in the research on schooling.

The R-squared statistic shows that marks in compulsory school are much better to predict the PISA scores than parental education combined with the other explanatory variables. The F-statistics for the joint significance of the parameters show that the null hypothesis of weak instruments is rejected (according to Staiger and Stock (1997), who recommend a critical value of 10).

The predicted values from first stage regressions for the literacy scores in Table 3 are used in the second stage regressions, which are displayed in Table 4, Panel A. Columns 1 to 4 contain the results for the multivariate regression of the PIAAC literacy score on the PISA literacy score and schooling when the PISA literacy score is instrumented, while the schooling variable is not instrumented.

Table 4 around here

Column 1 applies the variables in Table 3, column 1 as instruments, that is, the marks in compulsory school are used as instruments. The result is a coefficient of 0.68 on the PISA reading score, and a coefficient of 0.03 on the schooling variable. The coefficients are almost the same in column 2, where parental educational background and other instruments from Table 3, column 2 are used as instruments. This is also the case when both marks and parental background enter as instruments in column 3 and when the register variable for schooling is included in column 4 (the corresponding first stage regressions in Table 3 are contained in columns 1, 2, 3 and 4).

The skill persistence estimate of 0.70 in Table 4, column 4 shows an increase by 0.22 compared to the corresponding OLS estimate at 0.48 Table 2, column 3. The estimate of skill persistence in Table 2 is biased downwards as a consequence of measurement errors in the skill variable and instrumentation of this variable thus increases the estimate of skill persistence. However, the estimate of skill persistence in Table 2 is also biased upwards as a consequence of measurement errors in the schooling variable and this bias remains when the skill variable is instrumented, and the estimate at 0.70 is thus an upper bound of skill persistence (the expression for $\hat{\gamma}_x^{IV}$ in equation (15)). The OLS estimate of returns to education in Table 2, column 3 is 0.07 but this estimate decreases by 0.04 to 0.03 in Table 4, column 4 when the skill variable is instrumented. The instrumentation removes the upward bias of the OLS estimate of the returns to education due to measurement errors in skills but the downward bias due to measurement errors in the schooling variable remains and the estimate in Table 4, column 4 is thus a lower bound for the returns to education ($\hat{\beta}_x^{IV}$ in equation (16)).

Table 4, columns 5 to 7 contain the results when the schooling variable is instrumented. Column 5 applies both marks from compulsory school and parental educational background as instruments, column 6 uses the register schooling variable as instrument, and column 7 uses all available instruments (the corresponding first stage regressions in Table 3 are contained in columns 5, 6 and 7). The estimate of skill persistence becomes slightly higher when the schooling register variable is included as an instrument, while the returns to schooling become slightly lower.

The point estimate of skill persistence of 0.43 in column 7 is a decrease by 0.05 compared to the corresponding OLS estimate of 0.48 in Table 2, column 3. Instrumenting removes the upward bias of the OLS estimate due to measurement error in the schooling variable but the downward bias due to measurement errors in the skill variable remains, and the point estimate of skill persistence in column 7 is thus a lower bound for skill persistence ($\hat{\gamma}_S^{IV}$ in equation (17)). Returns to schooling is estimated to 0.12 in column 7, which is an increase by 0.05 compared to the corresponding OLS estimate at 0.07 Table 2, column 3. The downward bias in the OLS estimate due to measurement errors in schooling is removed by the instrumentation but the upward bias due to measurement errors in skills remains and the point estimate is thus an upper bound of returns to schooling ($\hat{\beta}_S^{IV}$ in equation (18)).

Table 4, column 8 contains the result when both the skill variable and the schooling variable are instrumented. The estimates of skill persistence of 0.62 and returns to schooling of 0.07 are consistent, given the validity of the instruments

The instrumental variable estimates form the basis for recovering the four bias terms of the parameters in the multivariate regression. The results of the two procedures described in the methodology section are close and for the sake of brevity the following only contains the results from the procedure that solely rely on differences between the IV estimate in Table 4.

When the skill variable is instrumented by the full set of instruments, but the schooling variable is not instrumented, the estimate of skill persistence at 0.70 in column 4 is biased upwards as a consequence of measurement errors in the schooling variable, while the estimate at 0.62 in column 8 is consistent as both variables are instrumented. The difference between the two estimates of 0.08 is thus an estimate of the bias in skill persistence due to measurement errors in schooling (denoted $\hat{\gamma}_x^{IV} - \hat{\gamma}_{xS}^{IV}$ in the methodology section), amounting to a bias of 13 per cent.

When the schooling variable is instrumented, but the skill variable is not instrumented, the estimate of skill persistence of 0.43 in column 7 is biased downwards due to measurement errors in the skill variable, while the estimate of 0.62 in column 8 is not biased. The difference of -0.19 ($\hat{\gamma}_S^{IV} - \hat{\gamma}_{xS}^{IV}$), or 30 per cent is thus an estimate of the bias in skill persistence due to measurement errors in the skill variable.

The upward bias in skill persistence in the multivariate regression due to measurement error in the schooling variable is of moderate magnitude, while the downward bias due to measurement error in the skill variable is substantial. The net result is a substantial downward bias in skill persistence in the multivariate regression.

When the schooling variable is instrumented, but the skill variable is not instrumented, the returns to schooling of 0.12 in column 7 is upward biased due to measurement errors in the skill variable in contrast to the consistent result of 0.07 in column 8. The difference of -0.05 ($\hat{\beta}_S^{IV} - \hat{\beta}_{xS}^{IV}$), or 64 per cent is thus the estimate of the bias in schooling due to measurement errors in skills. Measurement errors in skills thus result in a large overestimation in the returns to schooling when only the schooling variable is instrumented.

Instrumentation of skills but not schooling yields an estimate of returns to schooling at 0.03 in column 4, which is biased downwards as a consequence of measurement errors in schooling, while the estimate at 0.07 in column 8 is consistent. The difference between the two estimates of -0.04 ($\hat{\beta}_x^{IV} - \hat{\beta}_{xS}^{IV}$), or 60 per cent, is thus an estimate of the magnitude of the bias in schooling due to measurement errors in the schooling variable. Measurement errors in schooling thus result in a large downward bias in returns to schooling when only the skill variable is instrumented. The point estimate becomes so small that it is not significantly different from zero – implying that post-compulsory schooling should not have a significant impact on adult skills, which is in contrast to the significant OLS estimates in Table 2.

The multivariate estimate of returns to schooling is thus affected by a large upward bias due to measurement errors in the skill variable, and a large downward bias due to measurement errors in the schooling variable. However, as the two biases have the same magnitude they cancel each other out and the multivariate estimate of 0.07 is identical to the consistent estimate obtained when both skills and schooling are instrumented.

The bias terms in the multivariate regression forms the basis for recovering the bias terms in the bivariate regressions as described in the methodology section. Calculations show that the coefficient of the regression of PIAAC literacy skills on PISA literacy skills (the correlation coefficient) is downward biased by 0.13 due to measurement errors in skills and upward biased by 0.08 due to omission of the schooling variable. The coefficient in the regression of PIAAC literacy skills on schooling is downward biased by 0.02 due to measurement errors in the schooling variable and upward biased by 0.12 due to the omission of the skill variable. The result is thus that the bivariate regressions yield a moderate downward bias in skill persistence and a substantial upward bias in returns to schooling.[9]

Table 4, column 9 shows the result when the female dummy is included as a variable in the second stage regression and both early skills and schooling is instrumented. The result is that skill persistence is estimated at 0.69 and returns to schooling at 0.07.

Table 4, Panel B contains the analogous estimations for numeracy, the PIAAC numeracy scores are regressed on PISA numeracy scores and schooling. The sample size in Panel B is smaller than in Panel A and the precision of the estimates thus smaller (for the sake of brevity, the paper does not show the first stage regressions for numeracy). The magnitude of the estimates is comparable to the ones for literacy in Panel A, as none of the coefficients in Panel B are significantly different from the ones in Panel A. When both early skills and schooling are instrumented and the female dummy included in the second stage regression, the results in column 9 are point estimates of skill persistence of 0.71 and of returns to schooling of 0.05.

The multivariate regression in the previous section yields a point estimate of skill persistence in literacy of 0.50, while the instrumental analysis in this section yields an estimate of 0.69, which is significantly higher than the OLS estimate. The magnitude of the instrumental variable estimate is in the high end, relative to other estimates of persistence in ability. The conclusion is thus that

[9] The downward bias in skill persistence is calculated as $\lambda_{\tilde{x}}\gamma = \left(1 - \hat{\rho}^2_{\hat{S}\tilde{x}}\right)\left(\hat{\beta}^{IV}_S - \hat{\beta}^{IV}_{xS}\right)$, where $\hat{\rho}_{\hat{S}\tilde{x}} = 0.55$ is the correlation between $\hat{S}$, predicted schooling from the first stage equation and skill measure $\tilde{x}$, while the upward bias is calculated as $\hat{\alpha}_{\tilde{S}\tilde{x}}\hat{\beta}^{IV}_{xS}$, where $\hat{\alpha}_{\tilde{S}\tilde{x}} = 1.07$ is the coefficient in the regression of $\tilde{S}$ on $\tilde{x}$. The downward bias in returns to schooling is calculated as $\lambda_{\tilde{S}}\beta = \left(1 - \hat{\rho}^2_{\tilde{S}\hat{x}}\right)\left(\hat{\beta}^{IV}_x - \hat{\beta}^{IV}_{xS}\right)$, where $\hat{\rho}_{\tilde{S}\hat{x}} = 0.67$ is the correlation between $\hat{x}$, predicted skills from the first stage equation and schooling $\tilde{S}$, while the upward bias is calculated as $\hat{\alpha}_{\tilde{S}\tilde{x}}\hat{\gamma}^{IV}_{xS}$, where $\hat{\alpha}_{\tilde{S}\tilde{x}}$=0.20 is the coefficient in the regression of $\tilde{x}$ on $\tilde{S}$.

skills, as measured by PISA at the age of 15, have substantial and lasting impact on skills in the adult ages.

The impact of post-compulsory schooling on adult skills is estimated at 0.08 standard deviations per year of education in the multivariate analysis in the previous section and the estimate of 0.07 applying instrumental variable analysis in this section is almost the same. This amounts to 1.1 points per year on the scale used to measure intelligence, and the estimate is thus in the lower end of the range of the estimates found in the previous literature mentioned in the introduction.

6. Robustness check

This section reports various forms of robustness checks of the results reported in the two previous sections. The robustness checks include alternative specifications of the presented models.

An important issue to examine is to what extent skill formation is complementary in the sense that skills produced at one stage of life raise the productivity of investment at subsequent stages (see e.g. Cunha and Heckman (2007)) – in the present case if increased skills in compulsory school raise the productivity of investment in post-compulsory education. This hypothesis is tested by including the interaction term between early skills and schooling in the regressions. When this interaction term is included in the OLS regressions reported in Table 2, the interaction term is insignificant, implying that there is no sign of complementarity of skill formation after compulsory school.

Both gender and immigrant status are predetermined variables that are not altered by compulsory schooling and these variables could thus appears to belong together in the regressions. However, immigrant status is not significant in the second stage regressions and is thus omitted.

A formal test for inclusion of variables in the second stage regressions is performed in the form of a test for the validity of the overidentifying restrictions. The residuals from the second stage regressions are regressed on the instruments in an auxiliary regression and the test statistics is the number of observations times the uncentered R^2 of the regression, see Davidson and MacKinnon (1993), p. 236. The result of this procedure, which is applied to the final model presented in Table 4, column 9, is that the validity of the overidentifying restrictions is rejected. On the basis of the t-statistics for the instruments in the auxiliary regression, different variables were included in the second stage regression. The restrictions are accepted if all of the following five variables are included in the second stage equation: the education of the mother, the marks in mathematics, mark math missing, mark science missing and the variable for not wanting to go to school. The point estimates of skill persistence and returns to schooling are very close to the ones in Table 4, column 9, except when the marks in mathematics are included.

The schooling measure in the survey is derived from the respondent's answers to a question about the highest obtained education according to the ISCED (B_Q01a for respondents with a Danish education and B_Q01a3 for respondents with foreign qualification). The mapping from the highest obtained education to the number of years of education was constructed by each participating country but the quality of the mapping might vary between the participating countries. As a check of the quality of the Danish mapping, the mappings from the questions to the schooling measure in the other Nordic countries was reconstructed and used to construct alternative Danish schooling measures based on the Finnish, Norwegian and Swedish mappings. The correlation between the Danish schooling measure and the measures based on the mappings in the other Nordic countries varies from 0.95 to 0.98. The model in Table 4, panel A, column 9 yields an estimate of returns to schooling of 0.07, when applying the Danish schooling measure, and re-estimation, applying the schooling measures based on the mappings in the other Nordic countries, yields coefficients of 0.07 and 0.08. The corresponding coefficient for the persistence in skills is 0.69, when the Danish schooling measure is applied, and varies between 0.67 and 0.71, when the schooling measures are based on the mappings in the other Nordic countries. The results of the paper using the schooling measure based on the Danish survey are thus robust to alternative mappings from survey questions on educational level to the number of years of education.

7. Discussion

The results of this paper are directly comparable to the results by Gustafsson (2016), who traces the relation between PISA and PIAAC scores in different countries over time. The data used in the analyses are two differences in skill scores for the countries that participated in the first wave of PIAAC: (1) the change in the PISA skill scores from 2000 to 2012, and (2) the difference between the PIAAC scores for the age category around 27 (those who were 15 in 2000) and the youngest age category (those who were close to 15 in 2012). The scores obtained in the different PISA surveys are measured on the same scale and are thus comparable over time, see OECD (2014), Annex A5, pp. 280-293. The average scores for countries that participate in PISA varies over time and Gustafsson (2016) thus traces these changes to differences in the average PIAAC scores for the corresponding cohorts.

The result is a partial correlation coefficient between early and late literacy of 0.49 and a coefficient of 0.47 between early and late numeracy, which is close to the OLS estimates of 0.48 to 0.51 in Table 2, column 3 in this paper. However, the data points in Gustafsson (2016), p. 71, are country averages in a sample consisting of 20 countries and the confidence intervals are thus necessary broad (the t-value associated with the point estimates is 2.66 for literacy, implying a 95 per cent confidence interval with a lower bound of 0.13 and an upper bound of 0.85, while the numeracy t-value is 2.07, implying a lower bound of 0.02 and an upper bound of 0.92).

The preferred instrumental variable estimator of persistence in literary skills in this paper of 0.69 is estimated much more precisely. The estimate is significantly higher than the point estimate of 0.49 in Gustafsson (2016).

The studies reviewed in the introduction typically compare test scores taken in primary school with test scores taken at about age 18. The number of years between the tests is thus typically smaller than the number of years between the PISA test and the PIAAC test in the data for this paper. The number of years between these tests is 12 years, which is larger than the time spend in compulsory school. If persistence in test scores or skills decreases over time the expectation is thus that the correlation between the PISA scores and the PIAAC scores is smaller than the correlation obtained between test scores from primary school and tests scores from about age 18. The results of the present paper, with respect to both skill persistence and returns to schooling, are thus not necessary comparable to the previous studies on the development of IQ from early school to tests taken about age 18.

One of the contributions of this paper is that it includes a measure of students' well-being in school as a determinant of skills and schooling. The measure does not appear to have any impact on the PISA skill level, but if students do not like to go to school, they do not pursue post-compulsory education to the same extent as students who like to go to school. This result underscores the importance of obtaining both a high skill level in compulsory school and that students are 'happy' going to school, in order to obtain a high adult skill level.

The results are that if students do not like to go to school, they do not pursue post-compulsory education to the same extent as students who like to go to school, while there appears to be no impact of the index on the PISA skill level. This result underscores the importance of obtaining both a high skill level in compulsory school and that the students are ‘happy’ going to school, in order to obtain a high adult skill level.

The preferred estimates in the paper are obtained by instrumenting both early skills and schooling, a procedure that has the potential to yield consistent estimates in the presence of endogeneity problems, such as the ones caused by measurement errors in skills and schooling. The paper develops and applies a procedure to assess the extent to which other estimates of skill persistence and returns to schooling are affected in both upwards and downwards direction due to measurement errors and omitted variable bias.

The raw correlation between late and early skills is smaller but not far from the consistent estimate of skill-persistence as the downward bias due to measurement error in skills is counteracted by the upward bias due to omission of the schooling variable. A multivariate regression of late skills on both early skills and schooling yields a skill-persistence estimate that is more downward biased than the bivariate estimate as a consequence of a larger downward bias due to measurement errors in skills and a smaller upward bias due to measurement errors in schooling. Instrumentation of schooling, but not skills, yields an even smaller estimate of skill-persistence as the upward bias due to measurement errors in schooling is removed. Conversely, instrumentation of skills, but not schooling, removes the downward bias due to measurement error in skills but the upward bias due to measurement errors in schooling is so large that the absolute value of the bias in the estimate of skill-persistence becomes larger than in the bivariate regression.

The returns to schooling is severely upward biased in the bivariate regression but takes the value of the consistent estimate in the multivariate regression as a large downward bias due to measurement errors in schooling is counteracted by a corresponding upward bias due to measurement errors skills. Instrumentation of skills, but not schooling, removes the upward bias but the downward bias remains and returns to schooling becomes insignificant, which leads to the inference that post-compulsory schooling should not affect adult skills.

The methodological part of this paper thus underscores the importance of taking measurement errors of both skills and schooling into account if reliable estimates are to be obtained on PISA, PIAAC and analogous data sets. The procedures to obtain reliable estimates include the instrumental variable regression technique applied in this paper and the techniques for correcting for measurement errors in regression models applied in for example Winship and Korenman (1997) and described in for example Fuller (1987).

8. Conclusion

This paper analyses the relationship between skills obtained in compulsory school and adult skills. It examines how much skills measured by the end of compulsory school persist in the adult ages and to what extent post-compulsory schooling contribute to further skills of the adult population.

The analysis is conducted on high quality data from the OECD, the PISA survey for school children that is linked to PIAAC data for adult Danes. These data are comparable across countries and the results of the paper are thus likely to have high external validity. The results of the PISA survey have got considerable attention among policy-makers around the world and have led to school reforms in some of the participating countries. It is thus of importance to evaluate to what extent PISA skills assessed at age 15 have lasting effects in the adult ages.

The paper analyse the relationship between early and late literacy and numeracy skills. The results for numeracy are not significantly different from the ones for literacy, but the numeracy estimates are obtained on a smaller data set and are thus not as precise as the ones for literacy.

The preferred estimate of returns to schooling is 0.07 standard deviations, that is, one more year of post-compulsory education results in an increase in the PIAAC literacy score of 0.07 standard deviations. This estimate is in the lower end of the estimates found in the previous studies reported in the introduction. However, the estimate implies that for example seven years of post-compulsory education beyond age 15 increase skills by about half a standard deviation, which is a sizeable magnitude.

The preferred estimate with respect to persistence in literacy is 0.69 standard deviations, that is, an increase in the PISA score on one standard deviation at age 15 years results in an increase in the PIAAC literacy score of 0.69 standard deviations at age 27 years. This estimate is fairly high and comparable to or higher than the analogous estimates of persistence in IQ among the studies reviewed in the introduction.

The estimate of persistence in skills provides a link not only from PISA skills to adult PIAAC skills but also to labour market outcomes, as PIAAC skills have well-documented and sizeable effects on labour market outcomes. The high estimate of skill-persistence in this paper thus underscores the importance of compulsory school education providing skills as assessed in for example PISA and the relevance of these types of assessments of skills among school children.

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Table 1. Descriptive statistics, means and standard deviations of variables

Variables:	Mean	Std. Dev.
PIAAC scores		
Literacy	293.7	36.7
Numeracy	297.6	41.9
PISA scores		
Literacy	497.4	97.2
Numeracy	515.4	84.9
PISA marks		
Reading	66.5	9.6
Reading missing	0.068	0.251
Math	67.0	10.3
Math missing	0.071	0.256
Science	63.2	10.0
Science missing	0.118	0.322
Female	0.495	0.500
Both parents foreign		
Foreign parents	0.046	0.210
Foreign parents missing	0.002	0.048
Father education		
High	0.355	0.479
Middle	0.412	0.492
Low	0.232	0.423
Father edu. missing	0.015	0.121
Mother education		
High	0.383	0.486
Middle	0.369	0.483
Low	0.247	0.432
Mother edu. missing	0.007	0.085
Number of books home		
Number	230.3	237.4
Books missing	0.031	0.174
Do not want go to school		
Don't want school	1.850	0.896
Don't want school missing	0.026	0.161
Father absent		
Father absent	0.185	0.388
Father absent missing	0.053	0.223
Quarter of birth		
First	0.243	0.429
Second	0.261	0.440
Third	0.277	0.447
Fourth	0.219	0.414
Year of schooling		

PIAAC	13.25	2.32
Register	14.56	2.34
Register missing	0.01	0.11
Age		
PISA	15.7	0.3
PIAAC	27.0	0.4
Number of observations	1,880	-

Note: sample weights are used to calculate the means and the standard deviations.

Table 2. Bivariate and multivariate regressions for PIAAC literacy skills and PIAAC numeracy skills

Variables:	(1)	(2)	(3)	(4)	(5)
Panel A. Literacy					
PISA literacy score	0.558*	-	0.481*	-	0.501*
	(0.025)		(0.029)		(0.028)
Schooling	-	0.168*	0.073*	-	0.078*
		(0.012)	(0.013)		(0.013)
Female	-	-	-	-0.072	-0.299*
				(0.047)	(0.036)
Intercept	0	0	0	0.035	0.148*
	(0.022)	(0.023)	(0.021)	(0.036)	(0.024)
R-squared	0.312	0.153	0.334	0.001	0.356
Panel B. Numeracy					
PISA numeracy score	0.565*	-	0.509*	-	0.479*
	(0.035)		(0.039)		(0.035)
Schooling	-	0.150*	0.065*	-	0.080*
		(0.016)	(0.016)		(0.016)
Female	-	-	-	-0.396*	-0.358*
				(0.075)	(0.060)
Intercept	0	0	0	0.192*	0.174*
	(0.025)	(0.029)	(0.026)	(0.048)	(0.034)
R-squared	0.320	0.118	0.339	0.039	0.369

Notes: Standard errors in parentheses. * denotes significance at the 5 per cent level. Least squares regressions weighted by sample weights. The literacy and numeracy scores are standardized to have mean zero and standard deviation one. The number of years of schooling is measured as deviations from the mean. The number of observations is 1880 in the literacy regressions and 1055 in the numeracy regressions.

Table 3. First stage regressions, dependent variables: PISA reading score and years of schooling

Dependent variable:	PISA reading score				Schooling		
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.204*	0.323*	0.206*	0.195*	0.462*	0.407*	0.367*
	(0.044)	(0.045)	(0.040)	(0.037)	(0.122)	(0.069)	(0.069)
Mark language	0.332*	-	0.307*	0.278*	0.473*	-	0.158*
	(0.028)		(0.026)	(0.025)	(0.066)		(0.046)
Mark language missing	-0.156	-	-0.167	-0.117	-0.648	-	-0.076
	(0.203)		(0.163)	(0.166)	(0.432)		(0.331)
Mark math	0.234*	-	0.209*	0.195*	0.229*	-	0.029
	(0.030)		(0.030)	(0.027)	(0.070)		(0.044)
Mark math missing	-0.386	-	-0.305	-0.296	0.247	-	0.373
	(0.214)		(0.182)	(0.189)	(0.423)		(0.337)
Mark science	0.180*	-	0.170*	0.150*	0.389*	-	0.153*
	(0.033)		(0.029)	(0.030)	(0.059)		(0.038)
Mark science missing	-0.338*	-	-0.310*	-0.268*	-1.087*	-	-0.737*
	(0.120)		(0.108)	(0.095)	(0.306)		(0.198)
Mother Education	-	0.195*	0.063	0.059	0.177*	-	0.081
		(0.036)	(0.035)	(0.034)	(0.079)		(0.057)
Mother education missing	-	-0.225	-0.083	-0.011	-1.853*	-	-0.900*
		(0.313)	(0.246)	(0.238)	(0.481)		(0.402)
Father education	-	0.152*	0.082*	0.073*	0.298*	-	0.175*
		(0.036)	(0.030)	(0.031)	(0.093)		(0.070)
Father education missing	-	-0.346	-0.287	-0.245	-0.42	-	0.103
		(0.221)	(0.154)	(0.148)	(0.573)		(0.277)
Immigrant	-	-0.434*	-0.320*	-0.330*	0.576	-	0.444*
		(0.152)	(0.143)	(0.140)	(0.361)		(0.199)
Immigrant missing	-	0.727	0.419	0.47	-0.098	-	0.665
		(0.516)	(0.449)	(0.409)	(0.706)		(0.519)
Books home	-	0.136*	0.063*	0.052*	0.178*	-	0.022
		(0.031)	(0.022)	(0.023)	(0.049)		(0.038)

Books home missing	-	-0.036	0.296	0.245	0.238	-	-0.178
		(0.163)	(0.156)	(0.158)	(0.393)		(0.247)
Father absent	-	-0.128*	-0.056	-0.024	-0.438*	-	-0.022
		(0.061)	(0.053)	(0.055)	(0.134)		(0.079)
Father absent missing	-	-0.248	-0.06	-0.024	-0.549	-	-0.423*
		(0.165)	(0.135)	(0.122)	(0.288)		(0.211)
Do not want school	-	-0.06	0.002	0.008	-0.136*	-	-0.069*
		(0.031)	(0.024)	(0.024)	(0.052)		(0.034)
Do not want school missing	-	-0.546*	-0.444*	-0.420*	-0.216	-	0.077
		(0.195)	(0.164)	(0.164)	(0.351)		(0.245)
Quarter of birth							
Second	-	-0.01	0.088	0.078	-0.11	-	-0.260*
		(0.077)	(0.065)	(0.064)	(0.157)		(0.105)
Third	-	-0.087	0.016	0.001	-0.015	-	-0.197*
		(0.072)	(0.060)	(0.059)	(0.137)		(0.088)
Fourth	-	-0.140*	-0.044	-0.049	0.053	-	-0.016
		(0.067)	(0.052)	(0.048)	(0.153)		(0.105)
Schooling, register	-	-	-	0.060*	-	0.797*	0.716*
				(0.012)		(0.017)	(0.019)
Schooling, register missing	-	-	-	-0.455	-	-0.013	0.086
				(0.356)		(1.395)	(1.088)
Intercept	-0.023	-0.071	-0.035	-0.03	13.237*	13.052*	13.242*
	(0.031)	(0.054)	(0.044)	(0.042)	(0.119)	(0.047)	(0.080)
R-squared	0.412	0.177	0.447	0.464	0.303	0.656	0.694
F-test	97.4	16.8	41.7	44.4	22.3	759.4	136.7

Notes: Standard errors in parentheses. * denotes significance at 5 per cent level. The F-test is a test of the joint significance of the regressors. Least squares regressions weighted by sample weights.
The following variables are standardized to have mean zero and standard deviation one: PISA reading score, Mark language, Mark math, Mark science, Books home, Do not want school. The number of observations is 1880.

Table 4. Two stage least square estimates. Dependent variables: PIAAC literacy score and PIAAC numeracy score.

Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Literacy									
PISA literacy score	0.678*	0.639*	0.697*	0.698*	0.369*	0.436*	0.430*	0.618*	0.688*
	(0.048)	(0.116)	(0.049)	(0.053)	(0.049)	(0.030)	(0.030)	(0.054)	(0.053)
Schooling	0.033*	0.041	0.03	0.029	0.177*	0.114*	0.120*	0.073*	0.072*
	(0.016)	(0.025)	(0.016)	(0.016)	(0.040)	(0.015)	(0.015)	(0.019)	(0.019)
Female	-	-	-	-	-	-	-	-	-0.360*
									(0.037)
Intercept	0	0	0	0	0	0	0	0	0.178*
	(0.022)	(0.022)	(0.023)	(0.023)	(0.022)	(0.021)	(0.021)	(0.022)	(0.025)
Panel B. Numeracy									
PISA numeracy score	0.849*	0.841*	0.810*	0.803*	0.467*	0.499*	0.491*	0.812*	0.712*
	(0.081)	(0.184)	(0.085)	(0.085)	(0.049)	(0.042)	(0.041)	(0.093)	(0.084)
Schooling	0.008	0.01	0.015	0.016	0.113*	0.077*	0.086*	0.011	0.046
	(0.022)	(0.028)	(0.020)	(0.020)	(0.038)	(0.023)	(0.022)	(0.028)	(0.027)
Female	-	-	-	-	-	-	-	-	-0.295*
									(0.063)
Intercept	0	0	0	0	0	0	0	0	0.143*
	(0.029)	(0.029)	(0.028)	(0.028)	(0.026)	(0.026)	(0.026)	(0.028)	(0.039)
Variable instrumented									
PISA score	+	+	+	+	-	-	-	+	+
Schooling	-	-	-	-	+	+	+	+	+
Instruments									
Marks	+	-	+	+	+	-	+	+	+
Other instruments	-	+	+	+	+	-	+	+	+
Schooling, register	-	-	-	+	-	+	+	+	+

Notes: Standard errors in parentheses. * denotes significance at 5 the per cent level. Sample weights are applied.
The PISA score in Panel A is PISA literacy and the PISA score in Panel B is PISA numeracy. "Marks" are the variables

for compulsory marks listed in Table 3, column 1 and 4. "Other instruments" are the variables listed in Table 3, column 2 and 5. The PIAAC scores and the PISA scores are standardized to have mean zero and standard deviation one. The number of years of schooling is measured as deviations from the mean. The number of observations is 1880 in the literacy regressions and 1055 in the numeracy regressions.