The return of schooling: a review of estimates with tests for publication bias, trends, data and estimation methods

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Abstract

In this paper, we provide an analytical review of previous estimates of the rate of return on schooling investments in France and measure how these estimates vary over time, with the nature of data and by estimation methods. According to Ashenfelter Harmon and Oosterbeek (1999) approach (denoted below AHO), we do not find evidence of reporting bias in the estimates and, after taking due account of this bias, we find that differences in estimation methods still exist. Differences of specification in earning functions have also to be taken into account as well as the composition of sample (male/female, public/private sector). We also find that estimated returns have been decreasing in France since the end of the 60' and suggest a "meta Phillips curve" as a challenging explanation for this evolution.

Keywords: Schooling/earnings relationship; Rate of return; Estimates

1 Introduction

The "success story" of the earnings function (Willis 1986) is still growing. The point whether correlations between schooling and earnings reflect the causal impact of schooling on earnings is widely admitted and no more really discussed.

The studies focus yet on some more precise estimations of the rate of return to allow discussion about the trend or the heterogeneity of this return.

The results of the estimations do not invalidate the "schooling model" of Mincer (1974) but they propose very heterogeneous measures of the return (Griliches, 1977; Guille et Skalli, 1999; Card, 1998; AHO,1999; Hanchane et Moullet, 1997). Hence, in the same paper, conditioning on the estimation method, the chosen specification, the sample characteristics, the estimate of the return could go from one to three.

To improve our understanding of the rate's heterogeneity in order to determine the "true" return of schooling, some survey studies were done (Griliches, 1977; Card, 1998, 2001 ; AHO, 1999; Hanchane et Moullet, 1999; Guille et Skalli, 1999).

Griliches (1977) pointed the main problems when estimating the mincerian function by OLS method. This estimation technique assumes that the explanatory variables are uncorrelated with the unobserved disturbance in the equation, which for various reasons might not be fulfilled. The return estimate is biased, downward, if an individual's ability affects earnings but is omitted from the earnings equation. The concern about the formulation of an

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estimate of the return to schooling is that ability may be associated with both wages and schooling. This result was reinforced recently by Card (1998, 2001). As a result, the IV methods are suggested to deal with the problem (Heckman, Vytacil, 1998).

In the French case, two surveys recently done (Guille and Skalli, 1999 ; Hanchane and Moullet, 1997 ; Boumahdi and Plassard,1992) obtain the same conclusions : downward bias on return for OLS because of the endogeneity of schooling. Nevertheless, the IV estimator could lead to an upward estimation if :

- Instruments are correlated with wages
- Instruments are weakly correlated with schooling, especially for instance parent's schooling
- A "reporting bias" which leads authors to "select" the most significant results (AHO, 1999)
- Individual heterogeneity is not taken into account (Card, 1998).

Another important point to stress is the type of data used in the estimation process. As pointed by Mincer (Riboud, 1978), the best data to fit the earning/schooling relationship are panel data because they allow to use the entire career of the employees in the estimation process. Using cross section data implies to make crucial assumptions on the stability of the level of labour productivity, stability of the distribution of schooling and so on … Another question about the use of cross section data is the interpretation of the "experience" coefficients. They do not only measure the return of "on the job learning" but also the variations in business cycle along the career of employees.

Panel data allow to deal with individual heterogeneity using IV methods to take into account endogeneity of schooling and experience (Guillotin, Sevestre, 1994).

Panel data estimates of schooling return are usually higher than cross section ones (Lillard Willis,1978 ; Lillard Weiss,1979 ; Guillotin Sevestre,1994)).

Another set of reasons could explain the heterogeneity of the return of schooling. Characteristics of the studies as sample size, period of observation, type of explanatory variables, sample composition or chosen specification of the earnings equation may probably modify the estimate of the schooling return.

Empirical works are not perfect replications. Some studies use only men or choose a linear relation between earnings and experience; Others prefer to use men and women in a quadratic specification of the experience earnings relation.

Consequently, the heterogeneity of the schooling returns could be understood by using three types of sources : the estimation methods and their caveats, the type of data and their use in order with the theoretical model, the choices of specification done by the authors.

Then, the questions of the "reporting bias" and of the "upward trend" in returns could be explored more accurately.

Here, we use methods common among statisticians, called ''meta-analysis,'' (Hedges et Olkin, 1985 ; Berkey et al., 1995) to test if estimated payoffs are sensitive to estimation method, data type or specification choice to provide a framework to determine whether our inferences are sensitive to reporting bias or to time period trend.

The paper is organized as follows : the next section tests the heterogeneity hypothesis and organizes the sources of heterogeneity in order to specify the factors of the meta-regression. The results of the meta analysis of the return to schooling in France are presented in section 3. Section 4 focuses on Hedges and AHO's test of reporting bias and propose a meta Phillips curve as a challenging explanation to the trend hypothesis.

2 The sources of heterogeneity in schooling returns

The estimations of the schooling return β comes from the mincerian earning function which could be summarized as follows :

$$\text{Log } W_t = a + \beta S_t + \varepsilon_t$$

Various specifications of this simplified earnings function were estimated by numerous papers. In the French case, twelve studies reporting 99 estimates between 3.6 and 19.8 percent were used on the period 1962 to 1992 (see appendix B for details).

A first approach is to compute the arithmetic mean of the 99 measures which is 8.2 % with a standard error of 3.5. This wide distribution is a first indication of heterogeneity.

2.1 The heterogeneity of schooling returns

A first step in understanding this heterogeneity is to split the sample in sub-samples according to estimation methods and data type.

Figure 1 : heterogeneity of schooling return
Mean and confidence intervals (95%) of the studies by methods and data

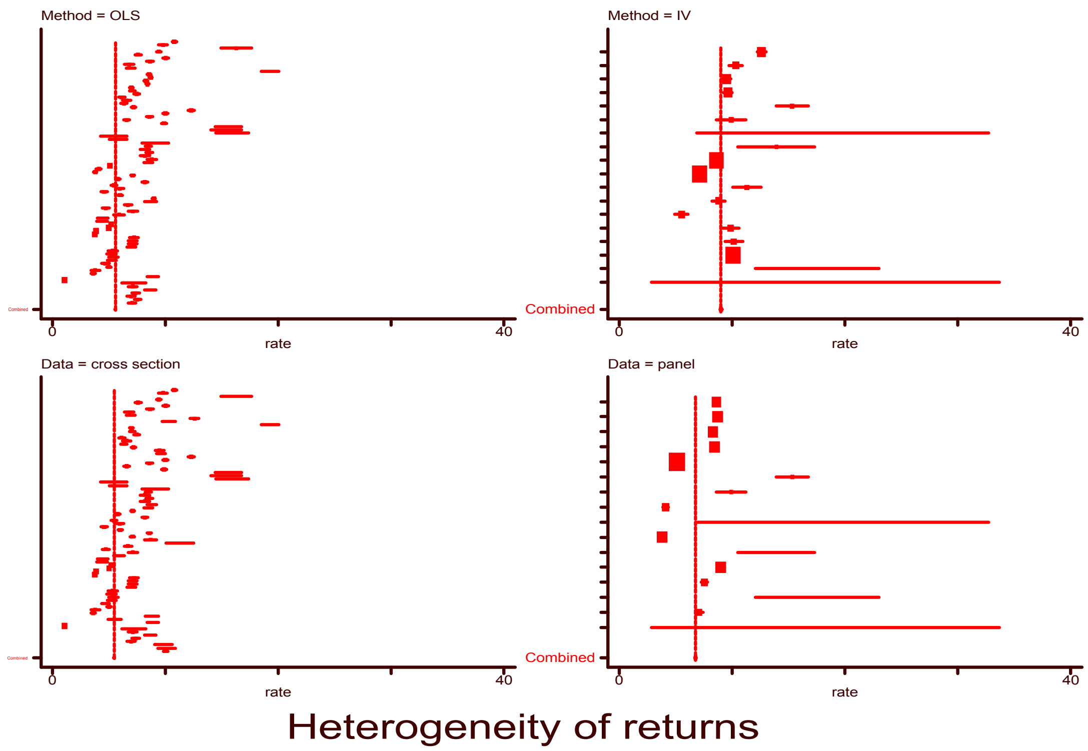


Figure 1 shows clearly that there is a large distribution of estimates, even inside the sub samples. According to AHO, the heterogeneity is higher using IV methods. We also can observe that Panel data lead to more heterogeneous estimations.

The nature of the random process followed by the parameter β becomes very important to choose the appropriate method of estimation (see appendix A for details).

Even if we take into account a pure random effect hypothesis instead of the fixed effect used by AHO the estimated mean return is significantly higher using IV methods or panel data.

Table 1 : heterogeneity of schooling return estimates

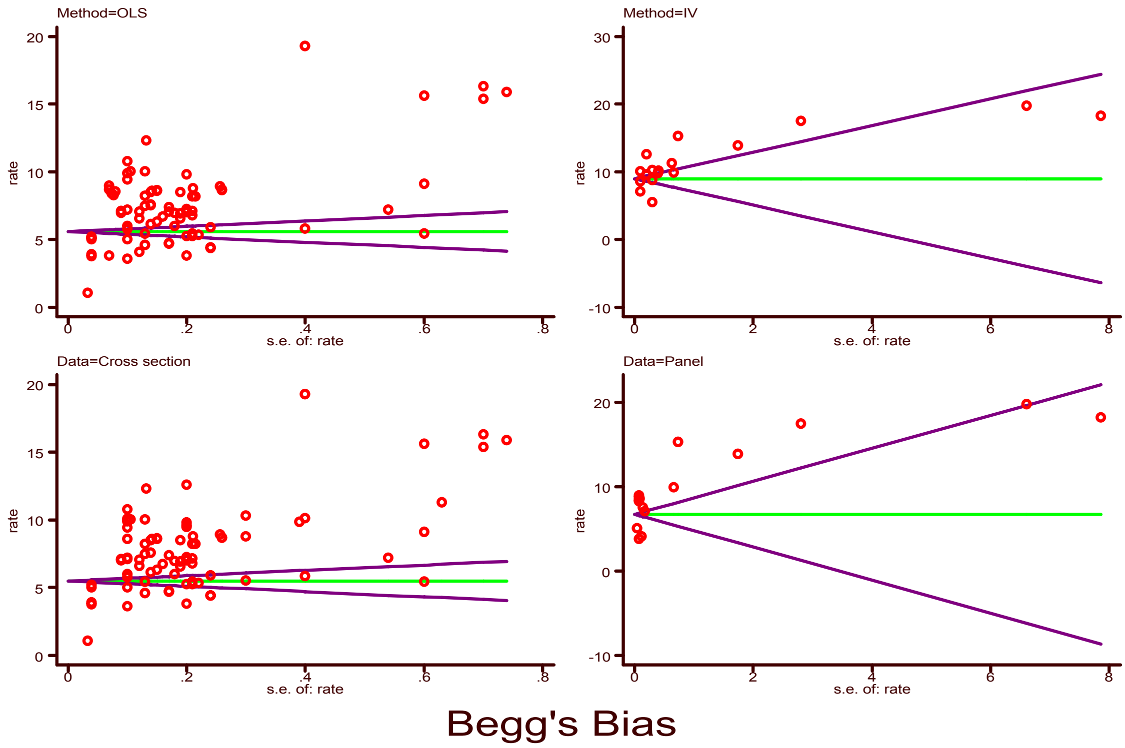
Process hypothesis	Pooled Estimates	By estimation methods		By data type	
		OLS	IV	Cross section	Panel data
Fixed effects (A1)	5.76	5.59	9.00	5.48	6.73
Pure Random effects (A2)	7.93	7.46	10.20	7.79	8.61

Using fixed effect hypothesis leads to lower estimations of the mean return whatever the sub sample is. These estimations of the schooling return are more precise than the simple arithmetic mean.

Another way to test the heterogeneity of the returns is to use the Begg's tunnel plot that gives the estimated mean as the horizontal line and the estimated confidence interval under the homogeneity hypothesis.

Each study is drawn, according to the sub samples. As forecasted, a lot of the studies are out of the confidence interval that underline the heterogeneity hypothesis.

Figure 2 : heterogeneity of schooling return : methods and data



2.2 The main sources of heterogeneity in schooling returns

The observed heterogeneity into the sub samples demonstrates that, apart of the estimation methods and the data type, other sources of heterogeneity could exist.

The first one, still pointed by AHO is the *omission of individual ability*. These one are non observable variables and their omission in the earning equation leads to an upward bias for β (Griliches 1977).

To solve this problem, proxis of ability like IQ test were used in the US but are not available in France. In the same way, twins samples are used to correct for innate characteristics (Ashenfelter and Krueger ,1994; Ashenfelter and Rouse,1998) but these types of data are not available in France.

Another solution to break down the correlation between schooling and the error term is to use instrumental variables for schooling like schooling achievement of the parents (Card, 1995; Miller and al, 1995; Conneely and Uusitalo, 1997; Ashenfelter and Rouse 1998).

The second source of heterogeneity is suggested by some studies (Baudelot et Claude, 1989; Goux et Maurin,1994) that focus on the *diminishing returns of schooling*. The idea is that high levels of schooling become more common in France (especially after some major change in education policy in the 80's) and lead to a diminishing return.

Another way to deal with this evolution is to "normalize" the observed level of schooling (Jarousse et Mingat, 1986). Usually, schooling is measured by the standard number of years of schooling. But, the "quality" of these years is not taken into account : for instance it is quite rare to be able to distinguish between certified and uncertified years of schooling.

Goux and Maurin [1994] and Hanchance and Moullet, [1997] show that "certified years of schooling" are the best indicator for human capital. The return of these certified years is double of the return for uncertified years. These results suggest a "sheepskin effect". The returns of certified years increase when this effect is taken into account in earnings function.

A third source of heterogeneity is the *way the authors specify the earnings equation*. The usual form of the earnings function could be thought as underspecified. Explanatory variables like experience or seniority are ignored. Since they are negatively correlated to schooling, the return is downward biased.

A "standard form" $\text{Log } W_t = a + \beta S_t + \beta_1 E_t + \beta_3 E_t^2 + \varepsilon_t$ is derived by Mincer (1974) from the human capital framework including experience as a measure of "on the job learning" and is very commonly used as the "Mincer's equation".

Some improvements could be offered to this basic specification in two ways : modifying the specification of earning/schooling relation or modifying the earning/experience specification.

Specification of earning/schooling relation :

- a "quadratic form" $\text{Log } W_t = a + \beta S_t + \beta_1 S_t^2 + \beta_2 E_t + \beta_3 E_t^2 + \varepsilon_t$ could be used to allow the return of schooling to decrease while accumulating human capital ($\beta_1 < 0$). Like other forms of capital, human capital (schooling) is supposed to exhibit a decreasing marginal productivity (Jarousse et Mingat, 1986; Plassard et Tahar, 1990).

- a "cubic form" $\text{Log } W_t = a + \beta S_t + \beta_1 S_t^2 + \beta_2 S_t^3 + \beta_3 E_t + \beta_4 E_t^2 + \varepsilon_t$ is sometimes used to try to take into account the non monotonicity of the return (Baudelot et Claude, 1989; Goux et Maurin, 1994). $\beta_1 < 0$ and $\beta_2 > 0$ allow to exhibit concave then convex earning/schooling relationship. This is a consequence of the increase of supply only for middle schooling in France at this period.

These improvements show more clearer the way the return to schooling is estimated in such studies. β is no more “the” return but we have to take into account β_1 and β_2 . For these studies, the return is computed for the mean value of schooling.

Specification of earning/experience relation :

- a “PURE form” : the PURE project use only earnings equation without experience that is a restricted form of the standard form and leads probably to “attribute” to schooling a return due to on the job learning.
- a “linear form” where experience is constrained to have a constant return.

The last source of heterogeneity lies in the sample composition. The sample used in the studies are different in various dimensions :

- Sample of men leads to higher returns than women’s sample. So the sample composition has to be included to understand the heterogeneity of returns.
- Sample of public sector earners leads to lower the earning/schooling return. In France, the high qualified people earn less in public than in private sector. Including public sector in the estimation would lead to lower earning/schooling relation.
- Sample using geographical or sectoral characteristics could take into account the specificities of local labour market because they don’t need the crucial hypothesis of unicity of the labour market (Harmon and Walker, 1995; Card ,1998)

We now turn to the meta regression to integrate all these sources of heterogeneity.

3 Meta analysis of the return to schooling in France

Extending the AHO innovative paper (1999), we use the Meta analysis approach to deal with the heterogeneity according to the sources the literature has pointed.

The main difference with the AHO case is that there is no sibling study in France. Another difference is that we do not use studies that take into account the measurement error problem on schooling. But the use of “normalized schooling” leads to control for the long-term increase of the level of human capital, which is especially important in France in the 80’s and 90’s.

We introduce some other sources of heterogeneity in schooling return like the type of data used, the sample composition and the specification choices of the authors.

Twelve studies providing 99 estimates of the return in the French case are used (See appendix B for details). In each study, various estimates were reported assuming various estimation methods, various specification of the earnings function or applying to different samples.

If minor differences occur in specification or sample the estimates are clearly correlated (Gelser and Olkin, 1994). To avoid a bias in the meta analysis, only one of theses estimate (the one chosen by the authors) is used in our sample.

The assumed meta independent variables are organized in the following table. Each of the items is numerous enough (Draper and Smith, 1980).

The sample composition meta variables (gender, private, public) indicate that the sub population is (item=1) in the sample used by the authors.

Table 2 : Meta independent variables

Meta independent Variable	Reference	Item
Trend	1962 = 0	1962 to 1996
Estimation methods	OLS = 0	IV = 1
Data type	Cross section = 0	Panel = 1
Sample size		Log N
Sample composition : gender	Men = 0	Women = 1
Sample composition : public	Public sector = 0	Public sector = 1
Sample composition : private	Private sector = 0	Private sector = 1
Specification: Sector dummies	Sector dummies = 0	Sector dummies = 1
Specification: quadratic Schooling	Schooling quadratic = 0	Schooling quadratic = 1
Specification: cubic Schooling	Schooling cubic = 0	Schooling cubic = 1
Specification: PURE no experience	PURE = 0	PURE = 1
Specification: linear experience	Exp linear = 0	Exp linear = 1
Normalized schooling	Norm schooling = 0	Norm schooling = 1

To implement this meta regression, we choose to use a random-effect regression model (A3 : appendix A) and a Maximum of Likelihood method of estimation because of the assumed heterogeneity of the return.

Table 3 : Meta regression of rates of return

	Coefficient	Standard error
"true" return	11.762	2.434
trend62	-.110	.024
Panel data	.116	.700
IV methods	3.927	.528
Women	-1.212	.455
Log N	-.363	.240
Public sector	-.217	.719
Private sectors	1.229	.476
Sector dummies	-3.401	.659
Spec: School Qua	2.800	.734
Spec: School Cub	.184	.742
Spec: Exp linear	-2.144	.819
Spec: PURE: No exp	4.119	.767
Normalized schooling	-1.042	.644
N	99	
Adjusted R 2	0.597	

The main results are not surprising:

- The "true" return of schooling, here in 1962, would be similar to the usual estimation. The returns seem to decrease to be around 7.3 in 2002.
- The IV methods lead to an higher estimate from 3.9 percent
- Using women data lowers return from 1.2 percent
- Private sectors return are higher than public ones
- Sectors dummies lowers returns from 3.4 percent
- Specification choices have significant impacts on the return estimates:
    - a quadratic form for schooling increases the estimated return
    - no experience in the earnings equation leads "to attribute" to schooling a very high return (PURE project)
    - a linear form for experience lowers the return of schooling.

4 Reporting bias, Estimation methods and trends in the schooling returns

Once taken into account the sources of heterogeneity, we can turn to the question of the « reporting bias ». We can suspect such a bias when results are published only if they seem « significant », that is, if the usual T test is high and the results in accordance with the "usual ones" (Hedges, 1992; AHO, 1999).

In such a case, the earning/schooling return is overestimated.

4.1 Graphical tests of reporting bias

Following AHO, we use the Egger's test as a first approach of the reporting bias.

Figure 3 : Egger's test for reporting bias

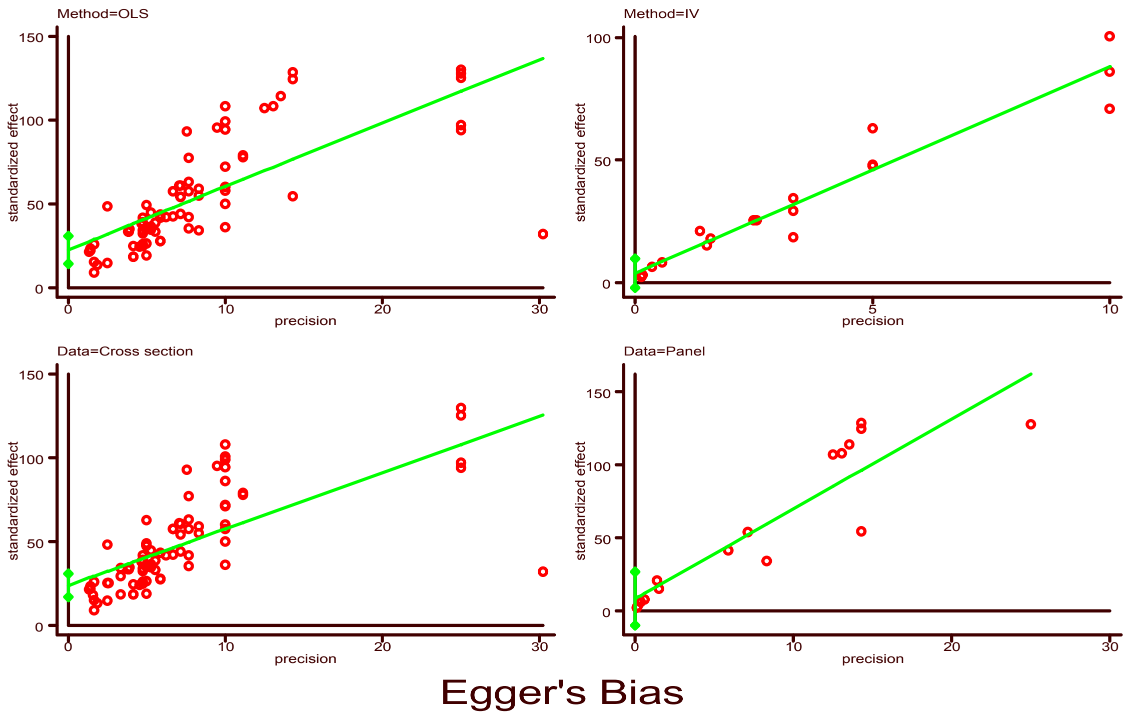


Figure 3 shows a plot of the estimated return against the standard error, together with the estimated regression line for each sub sample. In the absence of any selective reporting, this line should be horizontal, as the return to schooling should not vary in proportion to its standard error. If the tendency is to only report where the *t*-ratio is greater than 2 the estimated return will increase as the standard error increase in order to maintain the t-ratio above 2.

In each of the sub samples, the slope is significant denoting a reporting bias. However, according with AHO, IV methods exhibit a higher slope which is also the case for panel data. This is quite logical because of the easy use of IV methods in panel data studies.

4.2 Hedges and Ashenfelter's test of reporting bias

Hedges (1992) proposes a formal model of publication bias based on the assumption that exists a weight function based on outcome *p*-values which determines the probability a study is reported. The estimation procedure generates parameters that determine the increasing or decreasing probability of reporting a study. AHO (1999) specified different probabilities of observation of a study according to whether the *p*-value for that study is $0.01 < p < 0.05$ denoted ω_2 or $p > 0.05$ denoted ω_3, relative to a default category of $0 < p < 0.01$. This default category's weight ω_1 is normalized to unity 1 expressing the assumption that results with *p*-values in this bracket are reported with probability one. In the absence of reporting bias, ω_2 and ω_3 should equal unity as well, indicating the equality of outcome probabilities when significance of results is accounted for.

In addition to these parameters the overall pooled estimate for the return to schooling is provided based on the observed studies. Finally, the heterogeneity measured by the standard deviation in rates of return is estimated.

Table 4 : Hedges reporting bias test

Parameter	Unrestricted		Restricted ($\omega2=\omega3=1$)	
	Coefficient	Standard error	Coefficient	Standard error
$\omega2$	.771	.974		
$\omega3$	.044	.064		
"true" return	7.850	.325	7.958	.312
Log-likelihood	Log L unres	-162.434	Log L res	-165.413
N	99		99	

The test based on 2 (Log L unres – Log L res)) is a chi square test with 2 degrees of freedom. χ^2 is 5.96 just below the limit value of 5.99 and leads to reject the bias hypothesis.

The Hedges test gives the same results inside each of the sub samples by methods and data type.

AHO (1999) extended the Hedges test to take into account the heterogeneity factors used in the meta regression

Table 5 : Ashenfelter's extended reporting bias test

Parameter	Unrestricted		Restricted (ω2=ω3=1)	
	Coefficient	Standard error	Coefficient	Standard error
ω2	1.617	2.445		
ω3	.134	.236		
"true" return	11.619	2.443	11.762	2.434
trend62	-.111	.024	-.110	.024
Panel data	.033	.708	.116	.702
IV methods	3.873	.534	3.927	.530
Women	-1.218	.456	-1.212	.455
Log N	-.344	.241	-.363	.240
Public sector	-.222	.722	-.217	.719
Private sectors	1.216	.479	1.229	.477
Sector dummies	-3.384	.661	-3.401	.660
Spec: School Qua	2.791	.735	2.800	.734
Spec: School Cub	.201	.744	.184	.742
Spec: Exp linear	-2.138	.821	-2.144	.819
Spec: PURE: No exp	4.094	.768	4.119	.767
Normalized schooling	-1.026	.645	-1.042	.644
Log-likelihood	Log L unres	-103.325	Log L res	-104.623
N	99		99	

The AHO reporting test gives a χ^2 of 2.6 in this case. The hypothesis of a reporting bias has to be rejected. The same procedure was used for each sub sample but the correlation between some of the explanatory variables do not allow to obtain converging estimations.

With the same methodology, our results are opposite to those of AHO who observe a reporting bias especially for the IV estimations. The explanation of this divergence is probably due to the set of meta variables used in our meta regression. We include specifications choices of the authors, data type, and sample characteristics which are significant in the meta regression and explain probably part of the observed heterogeneity.

The result of a reporting bias in the US could be due to an under specification of the meta model. Another explanation could be a differing attitude of the authors towards the editorial process.

Another apparent difference between AHO and this paper is an increasing trend in the US and a decreasing one in France. We try in the next section to propose an explanation to this pseudo opposition.

4.3 From Mincer's earnings function to a Meta Phillips curve

The meta regression for French data is based, like the AHO's approach, on the assumption of a linear trend of evolution on the period.

We experimented some more flexible forms for the trend (quadratic then cubic) which give no successful results but suggest clearly a non linear profile of the trend. Returns seem to grow till the end of the 60's, then decrease till the late 80's and grow since the beginning of the 90's.

This suggests a "business cycle" evolution of the return. To illustrate this point, we estimate a meta regression using the unemployment rate as a "proxy" of the business cycle and replace the trend by this economic variable.

Table 6 : Meta regression of rates of return

Parameter	Trend of return		Meta Phillips Curve	
	Coefficient	Standard error	Coefficient	Standard error
"true" return	11.762	2.434	11.323	2.452
trend62 / Unemployment	-.110	.024	-.276	.066
Panel data	.116	.700	.049	.709
IV methods	3.927	.528	3.968	.535
Women	-1.212	.455	-1.217	.461
Log N	-.363	.240	-.337	.243
Public sector	-.217	.719	-.145	.727
Private sectors	1.229	.476	1.112	.477
Sector dummies	-3.401	.659	-3.464	.669
Spec: School Qua	2.800	.734	2.671	.745
Spec: School Cub	.184	.742	-.098	.748
Spec: Exp linear	-2.144	.819	-2.421	.832
Spec: PURE: No exp	4.119	.767	4.297	.770
Normalized schooling	-1.042	.644	-1.070	.653
N	99		99	

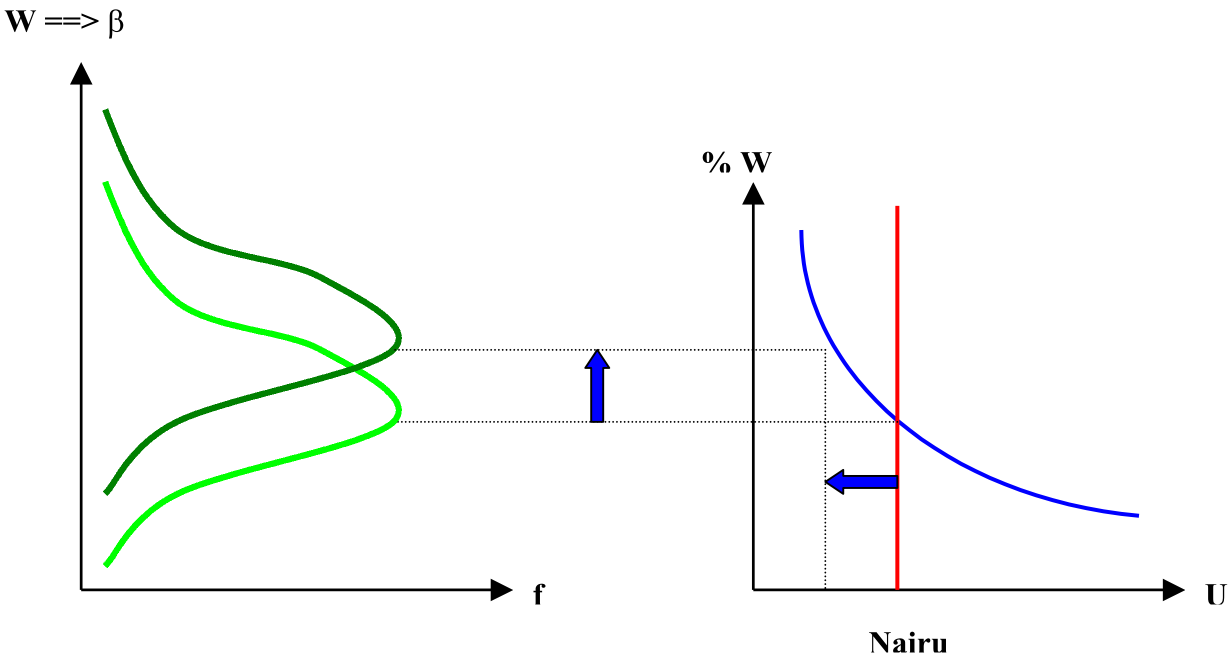
The results seem very similar between the two estimates concerning estimation's methods, data used and specification choices.

Two important differences occur:

First, the coefficient of unemployment rate shows that the higher the unemployment the lower the return. An increase of 4 points of the unemployment rate lowers the schooling return of 1 point. For instance, the NAIRU is calculated in France around 8% that leads to an "equilibrium rate of return" of 9.1%. The unemployment rate of 9% (France, end of 2002) would lead to a return of 8.8 %.

Second, the "true" return has no more an historical interpretation but could be understood in an economic perspective that is clearly connected with the Phillips' curve analysis. In long-term equilibrium, the NAIRU leads to an equilibrium level or distribution of wages (that is an equilibrium level for the return of schooling). If, in the short term, the unemployment rate decreases, wages increase and the distribution goes up. The distribution of schooling is stable and the return of schooling is increased.

Figure 4 : schooling return and Meta-Phillips curve



This hypothesis could be reinforced by the fact that Mincer's equations are very often estimated on cross section data.

The comparison between French ones and US results is also interesting. The data used in AHO describe wages in the 90's that is a decreasing period for unemployment in the US. Our data cover a long period between 1962 and 1994 with an important increase of the unemployment rate.

5 Conclusion

The heterogeneity of earning/schooling return observed in France, like in many countries, can be understood as follows :

1°) estimation methods give significantly different returns (higher for IV methods).
2°) data type used does not matter in the estimation of the return.
3°) earnings equation specification are crucial to determine a "true" return
4°) sample design has real consequences on the estimate

When accounting for these "technical aspects", we do not find a "reporting bias" in the French case. The bias observed in the US could be understood as the result of an under specification of the meta regression.

We propose a challenging explanation to the "historical trend" (increasing in the US, decreasing in France) by introducing an economic proxy of the labour market desequilibrium. The meta Phillips curve could explain the changes in apparent return of schooling and could lead to distinguish a short term return (the apparent one) and a long term return of schooling to be computed using the Nairu.

Appendix A : Methodology of Meta-analysis

The techniques of meta analysis are often used in medicine, psychology, management and more recently in economics (Card and Krueger, 1995, Stanley and Jarell , 1998; Stanley, 1998, AHO, 1999).

Among them, the random effect model has to be chosen to explore the systematic variations of the results on a given subject (NRC report, 1992 ; Cooper et Hedges, 1994, Berkey et al., 1995, Erez et Bloom, 1996).

The problem is to estimate the « true » value of a parameter β observed as $\hat{\beta}_i$ in independent studies i =1, 2,…, k. The choice of a statistical method is crucially determined by the assumptions done on the statistical process followed by the parameter.

Fixed effects model

The true parameter β is assumed to be the same in the different studies. So the estimates could be set as follows :

$$\hat{\beta}_i = \beta + \varepsilon_i \qquad \textbf{(A0)}$$

assuming $\hat{\beta}_i \sim N(\beta \,;\, \sigma_i)$ and $\varepsilon_i \sim N(0 \,;\, \sigma_i)$ **(A1)**

$$\text{Then } \hat{\beta} = \sum_i^k \hat{\beta}_i w_i \Big/ \sum_i w_i \qquad \textbf{(A2)}$$

with $w_i = 1/\sigma_i$

Fixed-effects regression model

To incorporate study covariates and thus account for heterogeneity among studies, one may further specify β by $X_i\alpha$, where X_i is a row vector that contains the values of the covariates for study *i* and α is a column vector of regression coefficients.

So, equation **(A0)** becomes $\hat{\beta} = X\alpha + \varepsilon$ **(A0')**

If $\hat{\sigma}_i$ is an approximately unbiased estimate of σ_i , then a weighted-least-square (WLS) estimate of α is $\hat{\beta} = (X'VX)^{-1}X'V\hat{\beta}$ with V= diag(w_i ……. w_k)

If we assume σ_i constant (homoscedasticity assumption), then OLS is appropriate.

Random-effects model

In this case the true parameter β_i follows a random process $\beta_i = \beta + \nu_i$ assuming $\beta_i \sim N(\beta ; \tau_i)$

The random term ν_i gives the measurement of the specificity of the i study.

Then , $\hat{\beta}_i = \beta_i + \varepsilon_i$ assuming $\hat{\beta}_i \sim N(\beta ; \sigma_i)$

Assuming ε_i and ν_i are not correlated, $\hat{\beta}_i = \beta + \nu_i + \varepsilon_i$ and $V(\hat{\beta}_i) = V(\varepsilon_i + \nu_i) = \sigma_i^2 + \tau^2$

If $\hat{\beta}_i \sim N(\beta, \sigma_i^2 + \tau^2)$

$$\text{then } \hat{\beta} = \sum_i^k \hat{\beta}_i w_i \Big/ \sum_i w_i$$

$$\text{with } w_i = (\sigma_i^2 + \tau^2)^{-1} \qquad \textbf{(A2)}$$

Random-effects regression model

A natural extension is to suppose that the true effect is depending on a set of study characteristics X ($X_{i1}, \ldots X_{im}$) : $\beta = X\alpha + \nu$

$$\text{Then, } \hat{\beta} = X\alpha + \nu + \varepsilon \qquad \textbf{(A3)}$$

The equation (**A3**) assumes that part of the variability in the true effects is unexplainable by the model. In contrast, the fixed-effects regression model supposes that the study characteristics account completely for variation in the true effect sizes ($\tau^2 = 0$). It has two components in its error term and so the variance of $\hat{\beta}$, controlling for the X's is:

$$V(\hat{\beta}_i) = V(\varepsilon_i + \nu_i) = \sigma_i^2 + \tau^2$$

The residual variance $V(\hat{\beta}_i)$ will be heterosedastic so long as ν varies across studies. It would clearly be inappropriate to use OLS to estimate both the unknown values α and τ^2. We consider only the iterative maximum likelihood approach to solve this problem. In large samples the estimates of ML are efficient. For other alternative estimators see Cooper et Hedges (1994) and Berkey and al. (1995). $\hat{\alpha}$ and τ^2 which maximize the following log likelihood function are the ML estimates of α and τ^2:

$$L = -0.5 \left(\sum_{i=1}^{k} \ln(\sigma_i^2 + \tau^2) - 0.5 \sum_{i=1}^{k} \left(RS \big/ \sigma_i^2 + \tau^2 \right) \right)$$

with RS the squared residuals of equation (3).

The equations **(A0')** and **(A3)** are called the meta-regression.

Publication Bias

Several methods for adjusting the meta-analysis for publication bias have been proposed using weighted distribution theory (Dear and Begg ,1992; Hedges , 1992, AHO (1999). Weighted distribution theory is based on the premise that a study is included in the analysis with a probability determined by the outcome (e.g. *p* value) (Dear and Begg, 1992). These selection probabilities are related to different possible outcomes via a weight function w(t). Then the probability density of $\hat{\beta}$ given that the study is published, G($\hat{\beta}$,β) is given by:

$$G(\hat{\beta},\beta)=f(\hat{\beta},\beta)\, w(t)/\int_{-\infty}^{\infty} f(\hat{\beta},\beta)w(t)\,dt$$

For more details see Hedges (1992), Dear and Begg (1992) and AHO (1999).

Appendix B : Sources for Meta analysis

Our analysis is based on the following studies.

Table B1 : studies used in the meta analysis

Authors	Date
Baudelot C. et Glaude M.	[1989]
Boumahdi R. Plassard J.M	[1992]
Guille M. Skalli A..	[1999]
Guillotin Y., Sevestre P.	[1994]
Goux D. Maurin E.	[1994]
Hanchane S. et Moullet S.	[1997]
Hanchane S. et Moullet S.	[1999]
Jarousse J.P. Mingat A.	[1986]
Plassard J.M. Tahar G.	[1990]
Riboud M.	[1978]
Sofer C.	[1990]

Table B2 : Descriptive statistics of the studies

Population	All		OLS		IV		Panel data		Cross section	
Variable	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Year	82.41	9.19	82.07	9.25	83.94	8.99	82.41	9.36	82.43	8.51
Log N	8.89	1.01	8.84	0.99	9.11	1.06	9.91	1.31	8.69	0.81
Return	0.082	0.035	0.075	0.030	0.115	0.039	0.104	0.36	0.078	0.031
Published (1=yes)	0.494	0.05	0.481	0.05	0.550	0.51	1	0	0.397	0.49
Sector (1=private)	0.290	0.45	0.296	0.46	0.277	0.46	0.25	0.45	0.301	0.46
Spec = quadratic	0.10	0.30	0.12	0.33	0	0	0.062	0.25	0.108	0.31
Spec = cubic	0.08	0.27	0.098	0.3	0	0	0.25	0.44	0.048	0.21
Exp = linear	0.08	0.27	0.098	0.30	0	0	0	0	0.096	0.29
Norm. School	0.09	0.28	0.086	0.28	0.11	0.32	0.125	0.34	0.084	0.27
Gender (1=female)	0.32	0.47	0.33	0.47	0.33	0.48	0.125	0.34	0.36	0.48
Number of studies	99		81		18		16		83	

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