

**Social returns to education:
Macro-evidence**

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Abstract

This paper presents new evidence on the social returns to education within a macroeconomic growth regression framework. I use improved schooling data and a macro version of the Mincer relationship between education and wages for individual workers. The results suggest that an increase by one year of the average education level of the labor force would increase labor productivity by 7-10% in the short run and by 11-15% in the long run. Some evidence is found for the presence of dynamic human capital spillovers: the human capital stock increases prospective economic growth. The empirical results are used to quantify the macroeconomic impact of skill upgrading as agreed upon in the European Union's Lisbon strategy for growth and jobs. Finally, the paper discusses discrepancies between private and social returns to education.

Key words: economic growth, panel data, returns to education

JEL Code(s): C33, I20, O40

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1 INTRODUCTION

The vast literature on private returns to education has consistently shown that schooling is a good investment. Schooling is a major input in the building up of human capital, and one additional year of schooling tends to increase a worker's wage by something between 5 and 15% (e.g. Psacharopoulos and Patrinos, 2004). A main argument for government subsidization is that education generates positive externalities, as for instance people exchange knowledge through social interaction outside the conventional market transactions (cf. Lucas, 1988). These human capital spillovers drive a wedge between social and private returns to education. Consequently, individuals cannot reap the full benefits from their educational investments, which may lead to underinvestment from a social viewpoint. Government subsidization of education will reduce the gap between private and social returns, so that the individual incentives to invest in education are no longer distorted. The key question here is how large are the social returns to education?

There are basically two different approaches to study the size of social returns to education. The first is connected to the empirical growth literature. Income differences across countries and over time can be explained from differences in factor inputs used in production and differences in the productivity of these inputs. Especially since the study by Mankiw, Romer and Weil (1992), there is a large literature on the role of human capital in explaining economic development. The second approach to estimate social returns to education is based on the idea that in addition to the individual benefits, human capital has characteristics of a local public good. In that case the average human capital stock in a region will have an effect on the productivity of workers in that region. Mincerian regressions including a proxy for average educational attainment in the area where the individual works or lives can then give insight into the quantitative importance of such human capital externalities (cf. Rauch, 1993; Acemoglu and Angrist, 2001; Ciccone and Peri, 2006).

This article follows the first approach. Many growth regressions failed to produce robust and plausible macroeconomic impacts of human capital. Two important explanations for this are measurement problems and misspecification of the relationship between schooling and human capital (cf. Krueger and Lindahl (2001), and Wößmann (2000)). Firstly, noise in schooling data leads to a downward bias in the estimated coefficients in growth regressions. Krueger and Lindahl (2001) evaluate the reliability of the most widely used data sets, showing that change in education is positively associated with economic growth once measurement error in

education is accounted for. This is confirmed in other studies, e.g. Temple (1999), Cohen and Soto (2001), De la Fuente and Doménech (2006), and Bassanini and Scarpetta (2001). Secondly, the regression model can be misspecified by assuming a linear relationship between schooling and human capital (cf. Wößmann, 2000). Instead, a large labor economics literature has confirmed that a log-linear specification gives the best fit to the data (cf. Card, 1999). Indeed, plausible estimates for the social returns to education are obtained when these aspects are taken into account.

Following up on these recent developments, I will provide some further empirical evidence on the social returns to education based on macro growth regressions in this paper. Briefly, my contribution is threefold. Firstly, I assemble a data set for a large number of developed and some medium-income economies from some state-of-the-art sources. In particular, I combine series on production per hour worked (the most direct indicator of labor productivity) available from the Groningen Growth and Development Centre and the high-quality educational attainment data constructed by Cohen and Soto (2001). A log-linear relationship between schooling and human capital is conjectured. This represents the macroeconomic equivalent of the standard Mincer equation in the labor economics literature. Secondly, the econometric analysis allows for both “level-level” and “level-growth” effects, the former referring to the relationship between the level of human capital and the productivity level and the latter referring to the relationship between the level of human capital and productivity growth. The level-level effect is due to the view that human capital is an ordinary input in the production process (as in Lucas (1988) and Mankiw, Romer and Weil (1992)), while the level-growth effect is linked to the notion that human capital increases a country’s absorptive capacity to assimilate new technologies (e.g. Nelson and Phelps, 1966). The respective coefficients provide guidance on the presence of static and dynamic human capital externalities. Thirdly, and finally, the analysis in this paper is put in a policy context. Some back of the envelope calculations on the economic impact of the human capital investment program within the EU Lisbon strategy for growth and jobs are provided. Also, by comparing social returns to education from macro-regressions with estimates of the private returns, I try to give an impression of the size of human capital externalities.

2 GROWTH MODEL WITH HUMAN CAPITAL

According to human capital theory (developed by Schultz (1961) and Becker (1964)), education enhances a person’s skill level and thereby his or her human capital. A higher skill

level in the workforce increases the production capacity. Although this sounds very straightforward, systematic research on how to incorporate human capital in theories of growth started only about two decades ago. In the 1990s the standard neoclassical growth model has been revised by introducing human capital, the standard references being Mankiw, Romer and Weil (1992) and Islam (1995). Consider that the production technology is determined from a Cobb-Douglas function, augmented by human capital

$$(1) \quad Y_{it} = A_{it} K_{it}^a (h_{it} L_{it})^{1-a}$$

where Y_{it} is production of country i in year t , A is total factor productivity, K is the stock of physical capital, h is the stock of human capital, L is raw labor, and α is the production elasticity of physical capital. Suppose that labor L and total factor productivity A grow over time with an annual growth rate of n and g , respectively. Human capital is built through schooling, and the relationship is given by a macro Mincer equation of the type

$$(2) \quad \log h_{it} = r S_{it}$$

where r is the return to education and S is educational attainment.¹ The growth rate of the labor force will vary across countries and over time, but technological progress g and physical capital depreciation δ are assumed to be constant. It can be shown that the testable empirical model is then given by

$$(3) \quad \log(y_{it}) = \frac{\alpha}{1-\alpha} [\log S_{it} - \log(n_{it} + g + \delta)] + r S_{it} + (h_i + t_t + e_{it}) / (1-\alpha)$$

where $y_{it} = Y/L$ refers to income per worker, and δ is the gross investment rate in physical capital. The first term in brackets on the right hand side is also referred to as adjusted investments, i.e. $\log S_{it}^{adj} \equiv \log S_{it} - \log(n_{it} + g + \delta)$. The panel data structure allows for

¹ The macro Mincer equation is the macroeconomic counterpart of the well-known Mincer equation standard in the labor economics literature, where the logarithm of the wage of a worker is explained from the worker's educational attainment and labor market experience, including as well a set of background characteristics such as gender, type of labor contract (e.g. full-time or part-time, fixed term or tenure), and sector of economic activity. Household surveys are used to econometrically estimate this relationship, where the estimated coefficient on educational attainment is interpreted as the private return to education. These types of regressions are also referred to as Mincerian regressions, and the estimated returns to education are called Mincerian returns. This all goes back to the seminal work of Jacob Mincer (1974).

country-specific intercept terms α_i and time dummies α_t . This equation is almost identical to the regression model in Soto (2002), where instead of the gross investment rate the capital-output ratio is included. As α corresponds to the capital share in output, which is in the order of magnitude of one third in a typical economy, the regression coefficient for log investments is expected to be around $\frac{1}{2}$.

The regression coefficient r on years of schooling S can be interpreted as the social return to education. The social rate of return to education is the macroeconomic counterpart of the private return to education, which is somewhere between 5 and 15%. In case of well-functioning markets and the absence of human capital externalities, private and social returns to education would be identical. The available empirical evidence suggests that private and social returns are more or less of the same size (there is at least no evidence for the existence of large discrepancies between both returns, see for instance Lindahl and Canton (2007) for an overview). So my guess is that r is between 5 and 15%. Indeed, Soto's results range from 7% to 10% (cf. Soto, 2002).

Notice that the macro Mincer specification assumes a linear relationship between the logarithm of human capital and years of schooling, so the point estimates are semi-elasticities. The log-linear formulation suggests that each additional year of schooling of the labor force increases productivity by r percent. Many other studies assume a linear relationship between human capital and years of schooling, so that the regression coefficient corresponds to the output elasticity of human capital with an expected size of something like $\frac{1}{3}$ (cf. Mankiw, Romer and Weil, 1992). The regression model can be misspecified by assuming a linear relationship between schooling and human capital (I will get back to this below; see also the discussion in Wößmann (2000)).

Data

Data on educational attainment are taken from Cohen and Soto (2001, but the updated version available from the OECD website is used). Cohen and Soto estimate school attainment for 5-year age-groups in 10-year intervals for 95 countries, utilizing OECD, national or UNESCO censuses, extrapolating missing observations. Sometimes they rely on enrollment data when census data is missing. This is probably the best existing data set on education for a large number of countries to date. For labor productivity y I use time series on output per hour worked available from the Groningen Growth and Development Centre. The Groningen

Growth and Development Centre also provides series on output per capita or output per worker, but as employment rates and hours worked vary across countries and over time, production per hour worked is the most appropriate indicator for labor productivity (the Annex briefly discusses the differences between the three indicators and their econometric implications). Data on population growth are also obtained from the Groningen Growth and Development Centre. Gross investment rates are taken from Penn World Tables (version 6.2). As investment rates are rather volatile, I use average investment rates. For 1960 I use the average investment rate between 1950 and 1960, etc. Following Mankiw, Romer and Weil (1992), the sum of technological progress and capital depreciation is set at 0.05. Combining the various sources enables the construction of a data set for 31 (mostly developed) countries for the years 1960, 1970, 1980, 1990 and 2000 (though data are not always available for all years).

Table 1: Summary of the data set

| Variable | Observations | Mean | Standard deviation | Minimum | Maximum |
|---|--------------|-------|--------------------|---------|---------|
| GDP per capita (1990 \$) | 144 | 11707 | 5989 | 2247 | 28403 |
| GDP per worker (1990 \$) | 144 | 27399 | 11683 | 5266 | 57928 |
| GDP per hour (1990 \$) | 144 | 15.20 | 7.70 | 2.36 | 35.51 |
| Annual hours worked | 144 | 1890 | 214 | 1380 | 2424 |
| Investments (% GDP) | 144 | 21.97 | 6.63 | 6.97 | 48.52 |
| Population growth (%) | 144 | 1.27 | 1.07 | -0.44 | 5.08 |
| Educational attainment, 15-64 age group (years) | 144 | 8.89 | 2.75 | 2.14 | 13.12 |
| Educational attainment, 25+ age group (years) | 144 | 8.14 | 2.75 | 1.68 | 12.88 |

Countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States, Venezuela.

Table 1 presents a summary of the data set. GDP per hour worked is on average about US\$ 15 (1990 prices), and ranges from US\$ 2.36 in Turkey (in 1960) to US\$ 35.51 in Norway (in 2000). This highest productivity performance per hour worked goes together with the lowest

figure for annual hours worked (1380 hours), while most hours were worked in Singapore (2424 hours in 1970). Average educational attainment of the 15-64 population group (who is not studying) is almost 9 years for the full sample, and varies from 2.14 years in Turkey (1960) to 13.12 in the United Kingdom (2000). Years of schooling of population 25 and over (whether studying or not) is somewhat lower.

3 RESULTS

Table 2 presents results from fixed effects regressions. I use income per capita, income per worker and income per hour worked as dependent variables, and educational attainment for the groups 15-64 (not studying) and 25+ (whether studying or not). The results are very interesting, and almost perfectly match expectations. The results also broadly confirm the findings in Cohen and Soto (2001) and Soto (2002). The coefficient of adjusted investments is close to its predicted value of 0.5, so that the regressions reported in the table all produce estimates of \bullet of around one third. The estimated social returns to education are between 11 and 15%. These should be interpreted as long-term social returns, allowing for physical capital to adjust to changes in educational attainment. The short-term effect of an additional year of schooling is calculated as $r(1-\bullet)$, and is also reported in the table. These short-term social returns to schooling are closely in line with typical estimates of private returns to schooling (cf. Psacharopoulos and Patrinos, 2004), implying that there are no significant static externalities from human capital accumulation.

Table 2: Educational attainment and labor productivity level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Dep. variable: | GDP per capita | GDP per worker | GDP per hour | GDP per capita | GDP per worker | GDP per hour |
| $\log S_{it}^{adj}$ | 0.431*** (0.100) | 0.473*** (0.109) | 0.471*** (0.120) | 0.438*** (0.099) | 0.474*** (0.110) | 0.472*** (0.121) |
| S_{it}^{15-64} | 0.119*** (0.036) | 0.111*** (0.039) | 0.113*** (0.043) | | | |
| S_{it}^{25+} | | | | 0.151*** (0.044) | 0.122** (0.048) | 0.122** (0.053) |
| Obs. | 144 | 144 | 144 | 144 | 144 | 144 |
| R ² (within) | 0.86 | 0.81 | 0.83 | 0.86 | 0.81 | 0.83 |
| implied \bullet | 0.301 | 0.321 | 0.320 | 0.305 | 0.322 | 0.321 |
| short-term return to education | 8.34% | 7.55% | 7.69% | 10.49% | 8.28% | 8.32% |

Note: Estimations are based on fixed effects regressions. Standard errors in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level. Time dummies are included.

Of these “level-level” estimates presented in table 2, I consider regression (3) as the preferred regression model, as the dependent variable (GDP per hour worked) is the most direct measure for labor productivity, while the educational attainment variable pertains to the population in the age group 15-64 who is not studying (which is the most direct estimate of the educational attainment of a country’s labor force).

Specifying human capital

In the above presented regressions human capital is measured by educational attainment, i.e. the average number of years in formal education. Other studies have used alternative measures for human capital. Mankiw, Romer and Weil (1992) use the percentage of the working-age population that is in secondary school. Primary and tertiary education are not included. Also, enrollment rates refer to human capital investments, not stocks, and Wößmann (2000) mentions some reasons why these enrollment ratios may actually be a poor proxy for the relevant flows of human capital investments. Enrollment ratios in one year do not measure the human capital embodied in the labor force entrants of that year, but refer to the human capital acquired by students who may or may not participate in the labor force at some future time. Also, net investment flows would have to take account of the human capital content of the workers who are exiting the labor force that year. School enrollment ratios may thus be an inaccurate proxy for changes in the human capital stock.

To proxy for the stock of human capital that is currently used in production, it would be natural to measure the accumulated educational investment embodied in the current labor force. Barro and Lee (1993) present data on educational attainment for the population aged 15 and over, and Barro and Lee (1996, 2001) also include data for the population of 25 years and older. They use census/survey observations on educational attainment as benchmark stocks, and when this information is not available the authors generate a forward-flow or backward-flow by using a perpetual inventory method based on enrollment data. Portela, Alessie and Teulings (2004) show that the perpetual inventory method smoothes observations, thereby compressing the data.² The Barro-Lee data thus underestimate the true values of education.

² More precisely, Barro and Lee assume that the survival rate is independent of the education level. In most countries average educational attainment is rising, as younger generations are more educated. The particular

The discrepancy between the census data and the constructed non-census data is proportional to the time elapsed since the previous census, and Portela, Alessie and Teulings correct the education data by subtracting the estimated measurement errors from the Barro-Lee series. De la Fuente and Doménech (2006) construct an improved data set on educational attainment for OECD countries by removing sharp breaks in the Barro-Lee data and by exploiting a variety of sources not used by Barro and Lee. Table 3 presents growth regressions using the schooling data from Barro and Lee (2001) and De la Fuente and Doménech (2006). The data on average educational attainment in De la Fuente and Doménech (2006) pertain to the population aged 25 and over. For comparability reasons I therefore used the Barro and Lee series for the population of 25 years and older.

Table 3: Educational attainment and labor productivity level using alternative schooling data

| | (7) | (8) |
|--------------------------------|---------------------|---------------------------|
| Schooling data: | Barro and Lee | De la Fuente and Doménech |
| Dep. variable: | GDP per hour | GDP per hour |
| $\log S_{it}^{adj}$ | 0.453*** (0.124) | 0.285 (0.189) |
| S_{it}^{25+} | 0.025 (0.033) | 0.023 (0.069) |
| Obs. | 144 | 81 |
| R ² (within) | 0.82 | 0.91 |
| implied • | 0.312 | 0.222 |
| short-term return to education | 1.69% | 1.78% |

Note: Estimations are based on fixed effects regressions. Standard errors in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level. Time dummies are included.

Compared with regression (6), the results worsen dramatically. In regression (7) where the Barro and Lee (2001) schooling data are used, the coefficient of adjusted investments is comparable to the earlier results presented in table 2, but the estimated social return to schooling loses statistical significance. Regression (8) with the De la Fuente and Doménech (2006) educational attainment series yields insignificant estimates for both the coefficient of

survival rate assumption would thus underestimate the survival of more educated individuals, resulting in lower average educational attainment for the country as a whole.

adjusted investments and the returns to schooling.³ The conclusion from this exercise is that the Cohen and Soto (2001) schooling data yield the most plausible results. Generally, noise in the measurement of educational attainment leads to a downward bias in the regression coefficients, which may render the estimates of the returns to schooling insignificant. Indeed, Cohen and Soto (2001) calculate that their data and the data from De la Fuente and Doménech display the highest reliability ratios (i.e. the fraction of the variability of a measure that is due to the variability of the true variable). The reliability ratio for the Barro and Lee data is lower, which can explain the lower estimate for the returns to schooling in regression (7). Comparison with the data from De la Fuente and Doménech is hampered because the latter source only includes OECD countries.

The second explanation for why many growth regressions failed to produce robust and plausible macroeconomic impacts of human capital is related to misspecification of the econometric model. In particular, the assumption of a linear relationship between schooling and human capital made in many growth studies is in contrast with findings from the labor economics literature which have firmly confirmed that a log-linear specification gives the best fit to the data (cf. Card, 1999). To study the sensitivity of the regression results to the type of specification, I present in table 4 the empirical results when the model assumes a linear relationship between schooling and human capital. The results when the Barro and Lee data and the Cohen and Soto data are used imply no significant impact from human capital on labor productivity. A strong effect of human capital on productivity is found when the data by De la Fuente and Doménech (2006) are employed, but this coefficient seems implausibly large.⁴

³ In contrast, De la Fuente and Doménech (2006) and De la Fuente (2007) report sizable contributions of educational attainment to productivity. I shall next turn to an explanation for this discrepancy, namely misspecification of the relationship between schooling and human capital in their econometric approach.

⁴ Regression (11) reproduces the findings in De la Fuente (2007) of a large output elasticity of human capital. He reports estimates that range from 0.587 to 2.606 with an average value of 1.11, bringing him to the conclusion that the true value of the output elasticity of human capital is “almost certainly above 0.50, that is, at least 50% higher than the most optimistic estimate of reference in the previous literature” (De la Fuente, pages 16-17, 2007).

Table 4: Educational attainment and labor productivity level using a linear relationship between schooling and human capital

| | (9) | (10) | (11) |
|-------------------------|---------------------------------|---------------------------------|---------------------------------|
| Schooling data: | Cohen and Soto | Barro and Lee | De la Fuente and Doménech |
| Dep. variable: | GDP per hour | GDP per hour | GDP per hour |
| $\log S_{it}^{adj}$ | 0.442 ^{***} (0.124) | 0.442 ^{***} (0.123) | 0.381 ^{**} (0.168) |
| $\log S_{it}^{25+}$ | -0.034 (0.192) | -0.102 (0.163) | 1.675 ^{***} (0.434) |
| Obs. | 144 | 144 | 81 |
| R ² (within) | 0.82 | 0.82 | 0.93 |

Note: Estimations are based on fixed effects regressions. Standard errors in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level. Time dummies are included.

Does the stock of human capital affect economic growth?

An alternative view to the role of human capital in the process of economic development is that human capital increases a country's absorptive capacity to adopt state-of-the-art technologies. Nelson and Phelps (1966), Vandenbussche, Aghion and Meghir (2006) and Benhabib and Spiegel (1994, 2005) assume that the human capital stock influences the speed of technological catch-up and knowledge diffusion. To test this hypothesis I investigate the importance of the human capital level for productivity growth. Table 5 first shows the preferred regression model (3) estimated in growth rates. The results are closely comparable, cf. regression (12). The estimated social return to schooling is somewhat lower - which can be expected as measurement error present in educational attainment data is exacerbated when first-differenced so that there is a stronger downward bias of the regression coefficient - but still significantly different from zero at the 5% level. In model (13) lagged educational attainment is included to investigate whether this has an impact on labor productivity growth through the technology adoption channel. Surprisingly, the coefficient on lagged educational attainment is negative, but insignificantly different from zero. This coefficient may pick up a catch-up effect, as countries with low educational attainment are typically countries with low

labor productivity, and hence countries which may profit from economic growth through the catch-up mechanism. In that case the coefficient on lagged educational attainment suffers from omitted variables bias.

Table 5: Educational attainment (level and changes) and labor productivity growth

| Dep. variable: | (12) Growth GDP per hour | (13) Growth GDP per hour | (14) Growth GDP per hour |
|---------------------------|---------------------------------|---------------------------------|----------------------------------|
| • $\log S_{it}^{adj}$ | 0.466 ^{***} (0.081) | 0.458 ^{***} (0.082) | 0.230 ^{***} (0.082) |
| • S_{it}^{15-64} | 0.076 ^{**} (0.034) | 0.068 [*] (0.036) | 0.077 ^{**} (0.032) |
| lagged S_{it}^{15-64} | | -0.000 (0.001) | 0.003 ^{***} (0.001) |
| lagged $\log(y_{it})$ | | | -0.026 ^{***} (0.004) |
| Obs. | 113 | 113 | 113 |
| R ² (adjusted) | 0.24 | 0.24 | 0.41 |

Note: Estimations are based on OLS regressions. Standard errors in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level.

In (14) also lagged labor productivity per hour is included to capture the catch-up effect. This renders the coefficient on lagged educational attainment positive, and significantly different from zero at the 1% level. According to this estimation, a one year increase in average educational attainment of the workforce would lead to an increase in labor productivity growth of 0.3%-point. This can be labelled as a dynamic human capital externality. Though more research would be needed to establish their robustness, these regressions are interesting in that they suggest the presence of dynamic human capital externalities.⁵

4 THE RE-LAUNCHED LISBON AGENDA FOR GROWTH AND JOBS

Arguably one of the most comprehensive policy packages to strengthen economic performance is the Lisbon strategy for growth and jobs, initiated at the Lisbon summit of EU leaders in 2000. Part of this strategy is to increase investments in human capital. The May

⁵ Only few studies are available to compare this result of a dual role for human capital. An example is Portela, Alessie and Teulings (2004), who report estimated impacts from lagged educational attainment on productivity growth of a similar magnitude.

2003 Council agreed on specific targets, including a reduction of early school leavers, an increase in the percentage of persons who have completed at least upper secondary education, an improvement in reading literacy, increased participation in life long learning, and an increase in the number of graduates in mathematics, science and technology. Gelauff and Lejour (2006) analyze the economic impact of reaching these (and other) Lisbon targets by imputing the quantitative targets in a general equilibrium model (WorldScan). Specifically, Gelauff and Lejour calculate the associated increase in labor efficiency, which is imputed in the model as a labor productivity shock. Skill upgrading in light of the Lisbon strategy is computed to generate about 0.5% of GDP at EU level in 2025 compared to the baseline simulation. This impact is increasing to 1.7% of GDP in 2040 (notice that the full impact on educational attainment is only reached when the last “pre-Lisbon” cohort has retired from the labor force).

These effects are the joint contribution from the five skill targets mentioned above. Instead of using a computable general equilibrium model, I can use the empirical results from this paper in an otherwise comparable thought experiment, namely the calculation of the productivity gains if the Lisbon skill targets are reached. I focus on the upper secondary school completion target. The reason is that achievement of this target would probably have the largest impact on a country’s average educational attainment, as it directly affects the length of a student’s school career.⁶ Regarding the upper secondary school completion target, Gelauff and Lejour find that after 10 years labor efficiency would increase by 0.1% in the Nordic countries and the new member states, while Portugal (on the other side of the spectrum) would gain 1.3%. These impacts gradually increase until the full effect is reached after about 40 years (with for instance a labor efficiency gain of 1.7% in Portugal).

Whereas Gelauff and Lejour (2006) base the calculation of the labor efficiency shock on a sophisticated satellite model for WorldScan developed in Jacobs (2005), I use a simpler

⁶ Notice that also the target to reduce early school leaving will affect average educational attainment, but preventing early school leaving implies that students complete an upper secondary education degree (cf. Gelauff and Lejour, 2006), so in the modeling exercise no distinction between these two targets can be made. The reading literary target concerns a qualitative aspect of the education sector which cannot be studied in the context of the present analysis (but it should be noted that the importance of the quality of human capital for economic performance is acknowledged in recent research, see for instance Hanushek and Kimko (2000) and Hanushek and Wößmann (2007)). The lifelong learning target is mostly about (post-education) training activities, and the associated increase in human capital is not captured in the average educational attainment variable employed in this analysis. Finally, the European Union’s ambition to increase the total number of graduates in mathematics, science and technology not necessarily corresponds to an increase in the total number of students in higher education, as students may shift away from other disciplines.

approach. Specifically, I assume that students who completed upper secondary education (International Standard Classification of Education 3) have attended one additional year of formal education than students who completed education at the lower secondary level (ISCED 2). I furthermore assume that the students affected by the Lisbon reform do not continue their education after completion of the upper secondary level. These two assumptions in combination with the current share and Lisbon target for completing at least upper secondary school available from Jacobs (2005) are used to calculate the full impact on average educational attainment for the group of countries included in the WorldScan simulations, cf. the third column of table 6. For example, if Austria reaches the target of 89% of people aged 22 with at least upper secondary school, average educational attainment in Austria would rise by 0.03 years. Portugal witnesses the largest change, and average educational attainment in the Portuguese labor force is calculated to increase by 0.19 years (i.e. on average almost ten weeks of extra formal schooling). From the estimates presented in regression (3) (cf. table 2) it is then straightforward to calculate the labor productivity effects. In the fourth column the estimated productivity impact without adjustments of the physical capital stock is calculated by using a social return to education of 7.7%, while the last column presents the productivity effects after adjustments of the capital stock (using a social return to education of 11.3%).⁷ The labor productivity gains from achieving the upper secondary school completion target calculated from the estimated social returns to education in this paper are broadly in line with the results in Gelauff and Lejour (2006).

Finally, the question of policy effectiveness comes to the fore. Which policy instruments most effectively increase upper secondary school completion rates? Ideally, policy design is evidence-based, adopting an experimental or quasi-experimental research design to determine the causal impact of a particular intervention (see e.g. Webbink (2005) for a survey). The art here for national administrations and institutions like the European Commission is to assess the likelihood that the existing set of policy actions will suffice to reach the objectives.

⁷ To be on the conservative side, I use the results from regression (3), and not the ones from regression (11) allowing for dynamic human capital spillovers.

Table 6: Productivity impacts of reaching the upper secondary school completion target

| | Current share completing at least upper secondary education | Lisbon target completing at least upper secondary education | Increase in average educational attainment (years) | Productivity impact without capital adjustment | Productivity impact with capital adjustment |
|--------------------|---|---|--|--|---|
| Austria | 0.86 | 0.89 | 0.03 | 0.23% | 0.34% |
| Belgium-Luxembourg | 0.82 | 0.86 | 0.04 | 0.31% | 0.45% |
| Czech Republic | 0.93 | 0.94 | 0.01 | 0.08% | 0.11% |
| Denmark | 0.87 | 0.90 | 0.03 | 0.23% | 0.34% |
| Finland | 0.90 | 0.92 | 0.02 | 0.15% | 0.23% |
| France | 0.78 | 0.84 | 0.06 | 0.46% | 0.68% |
| Germany | 0.88 | 0.91 | 0.03 | 0.23% | 0.34% |
| Greece | 0.77 | 0.83 | 0.06 | 0.46% | 0.68% |
| Hungary | 0.86 | 0.89 | 0.03 | 0.23% | 0.34% |
| Ireland | 0.80 | 0.85 | 0.05 | 0.38% | 0.57% |
| Italy | 0.64 | 0.74 | 0.10 | 0.77% | 1.13% |
| Netherlands | 0.80 | 0.85 | 0.05 | 0.38% | 0.57% |
| Poland | 0.88 | 0.91 | 0.03 | 0.23% | 0.34% |
| Portugal | 0.38 | 0.57 | 0.19 | 1.46% | 2.15% |
| Slovakia | 0.96 | 0.96 | 0 | 0% | 0% |
| Slovenia | 0.88 | 0.91 | 0.03 | 0.23% | 0.34% |
| Spain | 0.62 | 0.73 | 0.11 | 0.85% | 1.24% |
| Sweden | 0.92 | 0.93 | 0.01 | 0.08% | 0.11% |
| United Kingdom | 0.74 | 0.81 | 0.07 | 0.54% | 0.79% |
| Rest EU | 0.91 | 0.93 | 0.02 | 0.15% | 0.23% |
| EU25 | 0.80 | 0.85 | 0.05 | 0.38% | 0.57% |

Note: Current shares and Lisbon targets are taken from Jacobs (2005).

5 COMPARING PRIVATE AND SOCIAL RETURNS TO EDUCATION

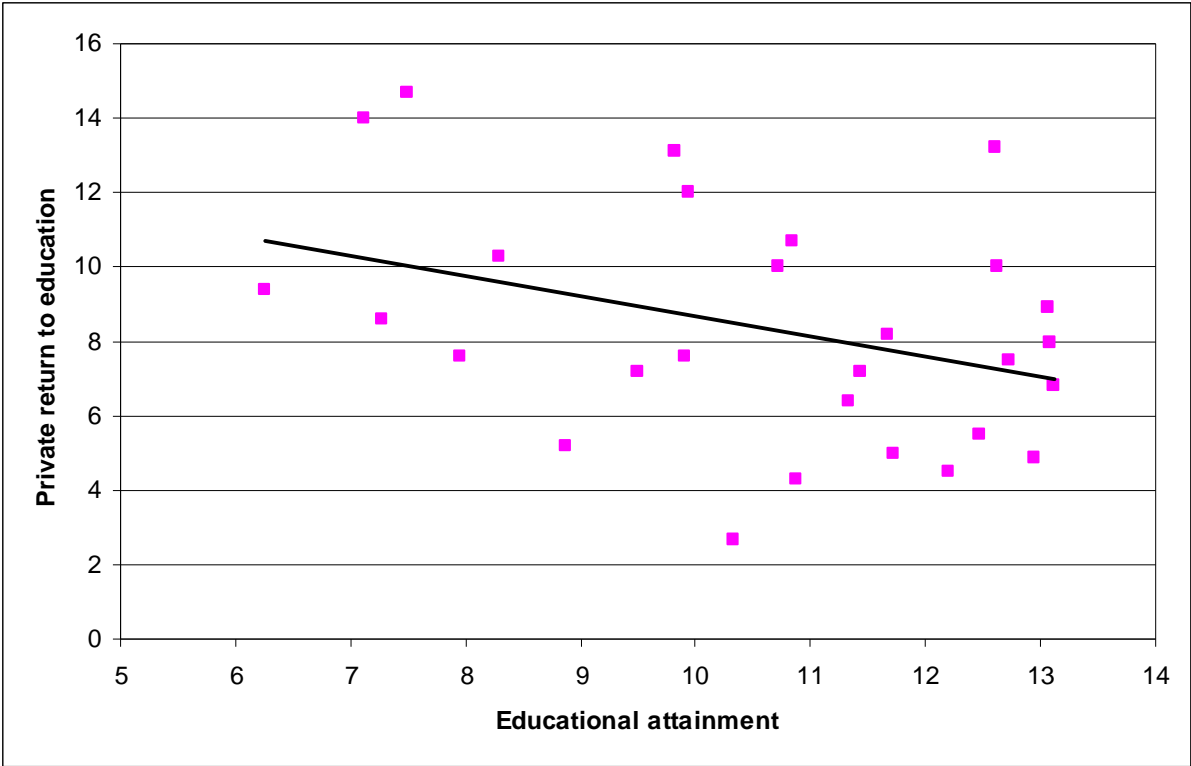
A central policy question is whether social returns to schooling exceed private returns. The results in section 3 suggest that the estimated social returns to schooling are approximately of the same size as the private returns, so there is no evidence that substantial human capital externalities prevail globally (i.e. for the full sample of countries). However, there might be substantial cross-country variations in these social returns. Jamison, Jamison and Hanushek

(2006) present country-specific social returns to education, and their results suggest that social returns are below the sample average in Argentina, Mexico and Turkey, while social returns are above the sample average in Belgium, Cyprus, Ireland and Singapore. Jamison, Jamison and Hanushek (2006) also compare their country-specific social returns to education to the private returns to education reviewed in Psacharopoulos and Patrinos (2004).⁸ In some countries there is an apparent imbalance between both returns. Argentina, Brazil, Colombia and Mexico have private returns in excess of the social return to education. Social returns in excess of the private return are observed for instance in Austria, Belgium, the Netherlands, Norway, Singapore and Spain. Such discrepancies between social and private returns may signal sub-optimal investment levels in human capital. This opens up a myriad of new research questions, such as how to intervene in education markets to restore optimal educational investments, which go beyond the scope of this paper. But I shall touch upon the question which education levels may generate the largest human capital externalities below.

To that end, let us look how these returns depend on levels of educational attainment. To get an impression of the importance of decreasing returns to education, I plot in figure 1 the private returns to educational investments reported in Psacharopoulos and Patrinos (2004) against educational attainment (15-64 age group) reported in Cohen and Soto (2001, figures pertain to the year 2000) for the sample of countries investigated in this paper (estimates for the private returns to education are not available in some cases). Indeed there is evidence that the private returns to education in countries with high educational attainment tend to be somewhat lower than the private returns in countries where schooling levels are lower. A simple OLS regression yields that the private return decreases by about 0.54%-point for each additional year of schooling (the regression coefficient is significantly different from zero, but only at the 10% level). This is somewhat smaller than the effect calculated in Harmon, Oosterbeek and Walker (2003), who report a reduction of about 1%-point for an additional schooling year in the population.

⁸ The private returns to education are based on studies of the determinants of individual earnings using household data, whereas the social returns are based on macro growth regressions. Such a comparison between private and social returns should therefore be interpreted with caution.

Figure 1: Private return to education and educational attainment



These decreasing returns may also play a role for the social returns to education, and can be captured by considering an adjusted macro Mincer equation of the type

$$(4) \quad \log h = \sum_a r_a S_a$$

where time and country indices are suppressed, and r_a is the social return to education corresponding to the level of education a . To implement this piecewise linear Mincer formulation, three levels of education are distinguished, 0-6 years, 6-10 years and more than 10 years of formal schooling (which roughly corresponds to primary, secondary and tertiary education), i.e.

$$\log h = r_1 S + r_2 S \cdot 1\{S > 6\} + r_3 S \cdot 1\{S > 10\}$$

where $1\{\cdot\}$ is the indicator function, taking the value 1 if the logical condition in brackets holds and the value 0 if not. Re-estimation of the preferred regression model (3) extended with such a piecewise linear Mincerian equation yields insignificant coefficients for the slope changes. The coefficients (standard errors) for r_1 , r_2 , and r_3 are 0.112 (0.053), -0.003 (0.015), and 0.010 (0.006), respectively. In other words, no evidence is found for the presence of decreasing social returns to education.⁹ To check the robustness of this result I also re-ran regression (14) with the piecewise linear Mincer equation. This yields similar findings (the regression coefficients of r_2 and r_3 are negative but not statistically significant). In other words, discrepancies between social and private returns to schooling tend to increase if a country has a higher average educational attainment. As such improved average educational attainment is typically induced by increased participation in tertiary education, a question for further research would be whether human capital externalities are more relevant at the right-hand side of the skill distribution.

6 CONCLUSIONS

Macro growth regressions for a group of 31 (mostly developed) countries yield estimates of a social return to education in the order of magnitude of 11-15%. So when average educational attainment of the labor force is increased by one year, the estimated impact on labor productivity is around 11-15%. This return shows little difference across the alternative productivity indicators used in this study (i.e. GDP per capita, GDP per worker and GDP per hour worked). These returns to education allow for adjustments in the physical capital stock, so they are to be interpreted as returns associated with balanced growth. Short-term returns to education where the capital stock is assumed to be fixed are in the range of 7 to 10%. The presented regression models also produce very plausible values for the production elasticity of physical capital. In addition to an impact of educational attainment levels on productivity

⁹ Few studies do take account of a piecewise linear Mincer specification. This is typically done by calculating average private returns to education at various education levels from review studies. For instance, Hall and Jones (1999) assume a rate of return of 13.4% for the first 4 years of education (this is the average rate of return Psacharopoulos (1994) reports for sub-Saharan Africa), a value of 10.1% for the next 4 years (the average for the world as a whole), and 6.8% beyond 8 years of education (which corresponds to the average rate of return in OECD countries reported in Psacharopoulos (1994)). I found only few studies where private returns to education are estimated allowing for a piecewise linear Mincer specification (e.g. Giles, Park and Zhang (2003), finding evidence for higher private returns to education for higher levels of education in China), and to the best of my knowledge there are no other studies where social returns to education are estimated using a piecewise linear Mincer specification such as equation (4).

levels, human capital is found to have a dual role in the sense that the human capital stock improves a country's capacity to assimilate new technologies in the spirit of the early work by Nelson and Phelps (1966). The conclusion of this exercise is that econometric estimations of the social returns to education using high-quality data on educational attainment and a macro Mincer relationship between human capital and years of schooling yield plausible results, which could feed into policy debates on the quantitative impacts of education policies. As an illustration I used the results to quantify the macroeconomic impact of reaching the target to increase upper secondary school completion as agreed upon in the European Union's Lisbon strategy for growth and jobs.

Finally, a comparison of the estimated social returns with private returns leads to the conclusion that private and social returns to education are roughly of equal size: no evidence is found for substantial human capital externalities. However, I hasten to add that human capital spillovers may certainly prevail in some countries. Indeed, Austria, Belgium, the Netherlands, Norway, Singapore and Spain seem to have social returns in excess of the private returns, with the apparent risk of underinvestment in schooling in these countries.

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Annex: Output per capita, output per worker or output per hour worked?

Most studies use series on output per capita or output per worker, but as employment rates and hours worked vary across countries and over time, production per hour worked seems the most appropriate indicator for labor productivity. Let us briefly look at the influence of the various choices on the regression results. By definition it holds that

$$\frac{GDP}{HOUR} = \frac{EMPL}{HOUR} \frac{GDP}{EMPL}$$

$$\frac{GDP}{HOUR} = \frac{POP}{HOUR} \frac{GDP}{POP}$$

Or, in logs,

$$\log\left(\frac{GDP}{HOUR}\right) = \log\left(\frac{EMPL}{HOUR}\right) + \log\left(\frac{GDP}{EMPL}\right)$$

$$\log\left(\frac{GDP}{HOUR}\right) = \log\left(\frac{POP}{HOUR}\right) + \log\left(\frac{GDP}{POP}\right)$$

While GDP/HOUR is the most obvious indicator for labor productivity, one can simply rearrange terms to express the regression model with GDP/POP or GDP/EMPL as endogenous variables. In a cross-country growth analysis, the average factor of proportionality (i.e. the sample average of $\log(EMPL/HOUR)$ or $\log(POP/HOUR)$) will affect the constant term, while country-specific deviations from that average will show up in the error term. If these country-specific deviations in the proportionality factor are correlated with the explanatory variables, the identifying assumption of Ordinary Least Squares estimation is violated and the regression estimates will be biased. Panel data estimation mitigates this problem, as cross-country differences in $\log(EMPL/HOUR)$ or $\log(POP/HOUR)$ would show up in the country-specific intercept term, and variations in these factors over time can be captured by time dummies. In other words, GDP/HOUR is the preferred indicator for labor productivity, but in a panel data setting with time dummies one would expect that the results obtained with GDP/POP or GDP/EMPL as dependent variables are closely comparable.