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Abstract

This paper proposes a method to estimate aggregate human capital externalities in a model of heterogeneous agents that imposes consistency between micro-level and macro-level Mincer returns to schooling. Externalities are estimated to be in the order of 1-5%, which are in line with the most recent findings in the literature.

Key words: Human Capital Externalities, Aggregation, Economic Growth

JEL classification: O1, O4, E1, C8

Resumen

Este trabajo propone un método para estimar externalidades del capital humano a nivel agregado en un modelo de agentes heterogéneos que impone consistencia entre los retornos a la educación de Mincer a nivel micro y a nivel macro. Se estiman externalidades en el orden de 1-5%, que son similares a los valores encontrados en los estudios más recientes de la literatura.

Palabras clave: Externalidades del capital humano, Agregación, Crecimiento económico

Clasificación JEL: O1, O4, E1, C8

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1 Introduction

The question of to what extent differences in human capital are able to explain income variations across countries has been a major concern for researchers and is still open. One clear indication of this relationship is given by the statistically significant correlation between income per worker and years of schooling. Figure 1 plots log output per worker versus years of schooling for a sample of 50 countries, averaged over the period 1960-1990. In fact, an OLS regression of log output per worker on years of schooling gives an estimated elasticity of 0.232, with standard error 0.028 and $\overline{R}^2 = 0.577$. A simple calculation suggests that there is room for human-capital externalities at the aggregate level. Assuming a Cobb-Douglas specification for production technology with a labor share of 0.64 for this sample of countries, the slope implied by Figure 1 is consistent with a social return to schooling of 0.148. With an estimated Mincer return to schooling of 9,6% (e.g., reported by Bils and Klenow (2000)), this implies an excess of social return to schooling over private returns of about 6%. We offer plausible explanations to account for this level of externalities. The novely of our approach is that we account for heterogeneity of human capital, both within and across countries.

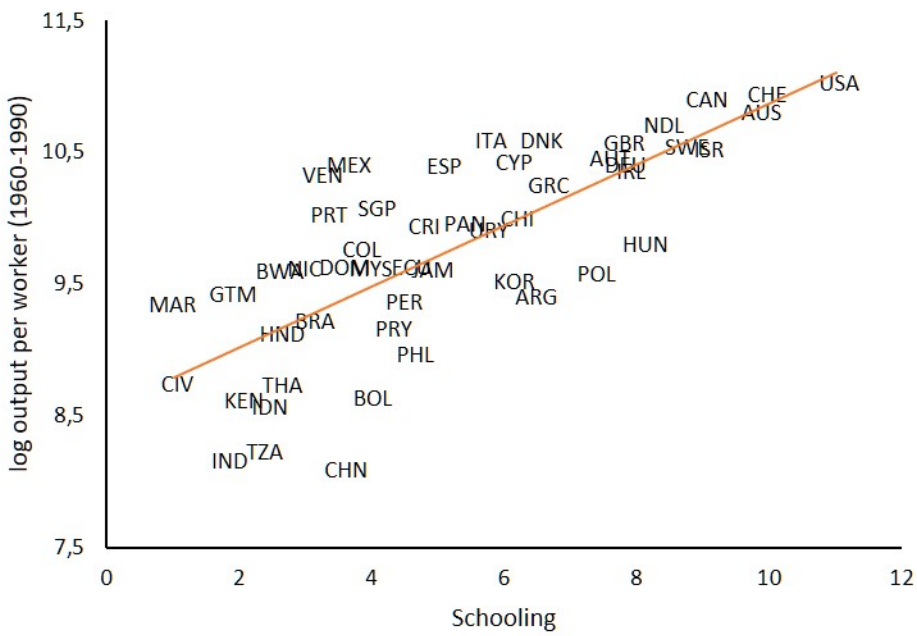


Figure 1: Log output per worker vs. years of schooling (1960-1990)

The relation between human capital and economic growth has a long standing in the economic literature. For instance, Benhabib and Spiegel (1994) run growth accounting regressions implied by a Cobb-Douglas aggregate production function, then human capital is insignificant in explaining per-capita growth rates. An alternative specification, with TFP depending on a country's human capital indicate a positive contribution for human capital. Klenow and Rodríguez-Clare (1997) and Bils and Klenow (2000) used Mincer regressions to estimate human capital and found that contrary to the *the neoclassical revival*, the view that output levels and growth rates are largely due to differences in physical and human capital, TFP differences have a more significant role than human capital. The work of Krueger and Lindahl (2001) and Cohen and Soto (2007) points out to measurement error in years of schooling. The latter finds no evidence of aggregate human-capital externalities.

In fact, we have learned a great deal from development accounting –the *proximate* role of physical capital, human capital, and TFP in accounting for income differences across countries– in the last thirty years. In a recent survey, Hsieh and Klenow (2010) find that human capital accounts for 10–30 percent of country income differences, physical capital accounts for about 20 percent, and residual TFP takes the largest part, accounting for 50–70 percent of country income differences. But they also stress the fact, as in Benhabib and Spiegel (1994), that TFP may have a role as an *indirect* determinant of variation in production factors (for example, due to differences in efficiency allocation) and recent studies have focused in that direction.[1] For instance, Manuelli and Seshadri (2014) compute the levels of TFP required to explain observed differences in output per worker, taking into account endogenous changes in all variables and the demographic structure, and found that the required differences in TFP do not exceed 35 percent. At the same time, output per worker is highly responsive in variations in TFP and demographic variables.

Heterogeneity and aggregation effects also play important roles. Several studies are based on average returns, which conceal substantial heterogeneity across countries. Using a large sample of countries, Soto (2009) shows that the causal effect of education on income is positive and statistically significant in countries with relatively high schooling quality. But on average macro Mincer coefficients are not larger than private ones. However, some of his results are similar to ours. For example, a GMM estimation produces an implicit labor share of about 0.54, which is higher than the one obtained in OLS estimations and also larger than the typical labor share used in the literature.[2] The implicit social Mincerian return (between 7.4% and 8.3%) is similar than the private return, but larger than other reported estimates. However, the author claims that this is an indication of absence of human capital externalities at the aggregate level.

The literature on externalities and growth has recently been surveyed by Klenow and Rodríguez-Clare (2005). Empirical evidence for human capital externalities is mixed. Early work find externalities to be in the order of 3 to 5%, but later Acemoglu and Angrist (2000) and Ciccone and Peri (2006) claimed that human capital externalities are very small or even negligible. Using a structural approach and compulsory schooling laws as an instrument, Guo, Roys, and Seshadri (2018) have recently found that an additional year of average schooling at the state level raises individual wages by about 6-8% in the United States.

Improvements in the availability of cross-country aggregate data from the last update of the

[1] Caselli (2016) argues that studies of development accounting are inadequate to investigate the nature of productivity differences, both across countries and over time, because technology is represented as being factor-neutral. The author supports the view that technology differences and technical change are typically factor-biased. We do not address this issue in this paper.

[2] We estimate an average labor share for our country sample of 0.57. See details below.

Penn World Table (PWT 9.1) in Feenstra et al. (2015) play an important part in our findings. In particular, the adjustment of labor shares to account for propietor's income proposed by Gollin (2002).

2 The Model

Suppose that agents are indexed by $i = 1, \ldots, L$ and $L > 0$ represents total labor force. Each agent has h_i units of human capital which are supplied inelastically in a competitive labor market at a wage rate given by w. Hence, labor earnings are defined as $\omega_i := wh_i$. Individual log-earnings are determined by a micro-level Mincer equation

$$\log \omega_i = \delta + \rho s_i + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i, \tag{1}$$

where s_i denotes years of schooling, x_i experience on the job, ε_i is an unobservable random variable, and δ, ρ, β_1, β_2, are constants.

A single representative firms operates a constant returns to scale aggregate technology of the form

$$Y = AK^\alpha H^{1-\alpha},$$

with $0 < \alpha < 1$ and produces in perfectly competitive markets. Define variables per-worker by

$$y := \frac{Y}{L}, \quad k := \frac{K}{L}, \quad \text{and} \quad h := \frac{H}{L}.$$

Therefore, output per-worker is given by

$$y = Ak^\alpha h^{1-\alpha}. \tag{2}$$

We assume that there are m population subgroups with sizes given by $L_j \geq 0$, $j = 1, \ldots, m$, and such that $L = \sum_{j=1}^m L_j$. To simplify, all agents in each subgroup j are identical, so $h_i = h_j$ for all $i = 1, \ldots, L_j$. Then, aggregate human capital H can be written as

$$H = \sum_{j=1}^m L_j h_j,$$

from which we immediately obtain

$$h = \sum_{j=1}^m \phi_j h_j, \tag{3}$$

where $\phi_j := L_j/L$ is the fraction of each subgroup in the labor force. Note that the micro-level Mincer equation (1) also holds for each j.

The wage rate is determined by aggregate conditions from the maximization problem of the firm, which yields

$$w = \frac{\partial y}{\partial h} = (1-\alpha) A k^{\alpha} h^{-\alpha}.$$

From (1), the above condition implies that

$$\log \omega_j = \log w + \log h_j = \log(1-\alpha) + \log A + \alpha \log k - \alpha \log h + \log h_j. \tag{4}$$

Consistency with the micro Mincer equation then requires that

$$\log(1-\alpha) + \log A + \alpha \log k - \alpha \log h + \log h_j = \delta + \rho s_j + \beta_1 x_j + \beta_2 x_j^2 + \varepsilon_j, \tag{5}$$

for each $j = 1, \ldots, m$. From (5), note that

$$h_j = \frac{e^{r_j}}{(1-\alpha)A} \left(\frac{h}{k}\right)^{\alpha}, \tag{6}$$

where

$$r_j := \delta + \rho s_j + \beta_1 x_j + \beta_2 x_j^2 + \varepsilon_j \tag{7}$$

are "private returns" to human capital investment as implied by the Mincer equation. By substituting (6) into (3) and rearranging terms, we obtain the following expression for aggregate human capital per worker

$$h = \left[\frac{\sum_j \phi_j e^{r_j}}{(1-\alpha) A k^{\alpha}}\right]^{\frac{1}{1-\alpha}}. \tag{8}$$

In what follows, these relations will be used to estimate a cross-country distribution of human capital and develop a methodology to measure aggregate human-capital externalities.

3 The Distribution of Human Capital

3.1 Data

We select 50 countries from the sample in Bils and Klenow (2000) based on data availability and for allowing comparison with existing studies. These countries are arranged in quintiles according to their output per worker y, averaged over the period 1960-1990.

Output per worker is calculated from the Penn World Tables (PWT 9.0) as output-side real GDP at current PPPs (cgdpo) divided by the number of persons engaged (emp). Estimates for k and A are obtained from the series of capital stock (ck) and TFP levels (ctfp), respectively. For each country, $(1-\alpha)$ is approximated as the average share of labor compensation in GDP at current national prices (labsh) for the years 1960-1990 (or the longest sub-period available).

Next, we combine the previous information with data on school attainment for total population between 25-64 years of age from Barro and Lee (2013). We follow Bils and Klenow (2000) and group them into six education categories $j \in \{\text{NO}, \text{LP}, \text{P}, \text{LS}, \text{S}, \text{T}\}$, corresponding to the following definitions: NO = No schooling, LP = Less than primary school completed, P = Primary school completed, LS = Less than secondary school completed, S = Secondary school completed, and T = Some tertiary school attained (or completed). Each category is assigned $s_j \in \{0, 3, 6, 9, 12, 14.5\}$ years of schooling, respectively. Mean age for each schooling category is constructed from population shares in the Barro-Lee data set, assigning the midpoint to each 5-year age group, i.e., $a \in \{27, 32, 37, 42, 47, 52, 57, 62\}$ and computing weighted averages for each j. Finally, work experience is approximated as $x_j = a_j - s_j - 6$, where a_j denotes age for group j.

Table 1: Country sample

Quintile	y_{US}	s	ρ	$1-\alpha$
5th (richest)	0.739	8.67	0.059	0.64
4th	0.491	5.57	0.088	0.55
3rd	0.289	4.95	0.099	0.58
2nd	0.201	4.23	0.122	0.53
1st (poorest)	0.091	2.72	0.109	0.54
All	0.362	5.23	0.096	0.57

A summary of the data is shown in Table 1. Income disparity between the top quintile and the bottom quintile is significant. In particular, the United States generates about 20 times the income per worker of the bottom quintile.[3] The gap in average years of schooling (s) is about 6 years. This is reflected in the fact that Mincer returns to schooling (ρ) tend to decrease with the level of income. Although labor shares ($1-\alpha$) do not show a discernible trend, the richest quintile has a larger share than the rest of the sample.

Table 2: Schooling

Quintile	ϕ_{NO}	ϕ_{LP}	ϕ_{P}	ϕ_{LS}	ϕ_{S}	ϕ_{T}
5th (richest)	0.032	0.111	0.260	0.181	0.261	0.155
4th	0.201	0.206	0.301	0.102	0.134	0.056
3rd	0.232	0.302	0.235	0.095	0.081	0.054
2nd	0.337	0.263	0.197	0.073	0.089	0.042
1st (poorest)	0.519	0.233	0.114	0.064	0.041	0.029

Differences in school attainment are startling. Only 3.2% of the top quintile population has no schooling, compared with 51.9% in the bottom quintile. Moreover, the share of the population with no schooling in the richest countries, from the top-left corner of Table 2 is nearly the same as

[3] Compared with Manuelli and Seshadri (2014), our sample misses many of the poorest countries, but it is also half the size of their country sample.

the share of the population with *some* tertiary education in poorer countries, which can be seen at the bottom-right corner of the table.

3.2 Development Accounting

Given that PWT 9.0 contains independent estimates for total factor productivity, we use the available data to estimate human capital per worker from aggregate technology. In particular, the series is constructed by solving for h in the following relationship implied by (2)

$$\log y = \log A + \alpha \log k + (1 - \alpha) \log h. \tag{9}$$

We also build an alternative measure for human capital per worker $\overline{h}$, under the assumption that $\alpha = 1/3$, a commonly used benchmark value in the literature. This may overstate the variation of human capital across countries. Results are summarized in Table 3 below.

Table 3: Development accounting

	Relative to the U.S.				
Quintile	y	A	k	h	$\overline{h}$
5th (richest)	0.739	0.884	0.732	0.924	0.891
4th	0.491	0.801	0.504	0.597	0.706
3rd	0.289	0.705	0.212	0.602	0.598
2nd	0.201	0.713	0.018	0.561	0.532
1st (poorest)	0.091	0.477	0.052	0.443	0.375

Note that differences in h (and $\overline{h}$) are in the same order of magnitude than differences in TFP. On the other hand, differences in output per worker are much larger and similar than the ones observed for physical capital per worker.

In order to evaluate the contribution of production factors and TFP to variations in income per worker, we follow Bils and Klenow (2000) and define the share contribution to log-income per worker from TFP, physical capital and human capital as

$$\Phi_A := \frac{\text{cov}(\ln y, \ln A)}{\text{var}(\ln y)}, \quad \Phi_k := \frac{\text{cov}(\ln y, \alpha \ln k)}{\text{var}(\ln y)}, \quad \text{and} \quad \Phi_h := \frac{\text{cov}(\ln y, (1 - \alpha) \ln h)}{\text{var}(\ln y)},$$

respectively. Clearly, (9) implies that $\Phi_A + \Phi_k + \Phi_h = 1$. Results are reported in Table 4.

Table 4: Share contributions

Model	Φ_A	Φ_k	Φ_h
α varies	0.302	0.173	0.525
$\alpha = 1/3$	0.302	0.429	0.269

Based on these estimates, we can conclude that keeping TFP differences constant and assuming $\alpha = 1/3$ for all economies diminishes the contribution of human capital nearly in half.

3.3 Human Capital and Schooling

Our measure of human capital per worker exhibits a strong correlation with years of schooling, as can be seen in Figure 2. In order to quantify this relationship, we estimate macro Mincer coefficients by regressing $\log h$ on average years of schooling (s) and work experience, approximated as $x = a - s - 6$, where a is obtained for each country as weighted averages using the weights from Table 4.

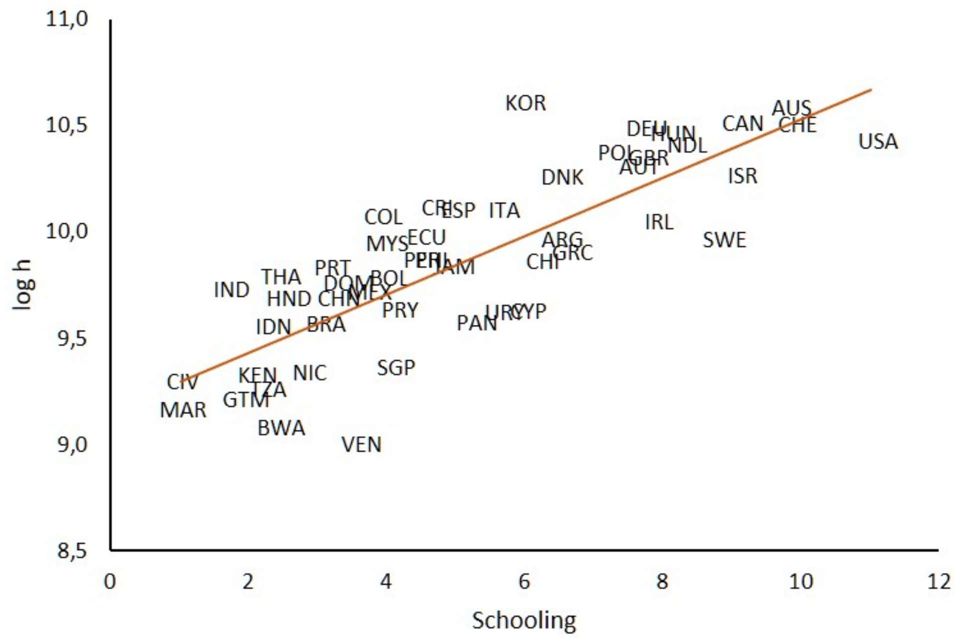


Figure 2: Log human capital per worker vs. years of schooling (1960-1990)

Table 5: Macro-level Mincer regressions

Indep. Variables	(1)	(2)	(3)
Intercept	9.153	8.420	9.435
	(0.081)	(0.521)	(3.806)
Schooling (s)	0.138	0.148	0.146
	(0.014)	(0.017)	(0.017)
Experience (x)		0.024	-0.046
		(0.017)	(0.258)
Exp. squared (x^2)			0.001
			(0.004)
$\overline{R}^2$	0.665	0.672	0.665
Number of countries	50	50	50

The results of the OLS regressions are reported in Table 5. In all cases, estimated coefficients on schooling are statistically significant at a 1% confidence level. Since the average micro-level Mincer coefficient for schooling (ρ) in the sample is 0.096, the range of estimates for the macro-level Mincer coefficient of schooling of 0.138-0.148 suggests that aggregate human capital externalities could be in the order of 4-5%, which is in line with the most recent estimates in the literature.

Another interesting observation from Table 5 is that column (2) shows a value for the return on experience (0.024) that is similar to those obtained from micro-level estimates, although is not statistically significant. In fact, the average return to experience β_1 in the country sample reported by Bils and Klenow (2000) is 0.049. However, column (3) shows that experience squared is not only insignificant for this aggregate specification, but also the coefficients on x and x^2 have actually the "wrong" sign. Linearity of the aggregate Mincer equation is also consistent with the works of Growiec (2010) and Growiec and Groth (2015).

4 Measuring Aggregate Human-Capital Externalities

In this section, we develop a method to measure human capital externalities that builds on the model of Section 2.

4.1 Methodology

To simplify, and to consider the effects of aggregation on the micro-level Mincer equation, assume that $\beta_2 = 0$ and let $\beta := \beta_1$.[4] We conjecture that, for given values of x_j, human capital is certain function of schooling, say $h_j = g_j(s_j)$, that satisfies condition (5). Thus,

$$\log(1-\alpha) + \log A + \alpha \log k - \alpha \log \left(\textstyle\sum_j \phi_j g_j(s_j) \right) + \log g_j(s_j) = \delta + \rho s_j + \beta x_j + \varepsilon_j, \tag{10}$$

for each $j = 1, \ldots, m$. Implicitly differentiating (10) with respect to s_j,

$$\frac{1}{h_j}\frac{\partial h_j}{\partial s_j} - \frac{\alpha}{h}\phi_j \frac{\partial h_j}{\partial s_j} = \rho,$$

$$\frac{1}{h_j}\frac{\partial h_j}{\partial s_j} - \alpha \frac{\phi_j h_j}{h} \frac{1}{h_j}\frac{\partial h_j}{\partial s_j} = \rho.$$

Therefore,

$$\frac{\partial \log h_j}{\partial s_j} = \frac{\rho}{1 - \alpha \psi_j}, \tag{11}$$

where

$$\psi_j := \frac{\phi_j h_j}{h}$$

[4] See Growiec and Groth (2015).

is the contribution of each subgroup j to aggregate human capital per-worker.

Note that each function g_j can be approximated from (11) as an exponential function of the form

$$h_j = Be^{\frac{\rho}{1-\alpha\psi_j} s_j}, \tag{12}$$

and $\tilde{\rho}_j := \rho/(1-\alpha\psi_j)$ can be taken as an estimate of a "social rate of return to schooling" for $j \in \{\mathrm{NO}, \mathrm{LP}, \mathrm{P}, \mathrm{LS}, \mathrm{S}, \mathrm{T}\}$.[5]

4.2 Results

For estimation purposes, condition (12) can be transformed into

$$\psi_j - \tilde{B}\phi_j e^{\frac{\rho}{1-\alpha\psi_j} s_j} = 0,$$

where $\tilde{B} := B/h$, so the estimates depend on parameters only and are independent of aggregate data. This, together with

$$\sum_{j=1}^{m} \psi_j - 1 = 0$$

form a nonlinear system of six equations in six unknowns $(\tilde{B}, \psi_{\mathrm{NO}}, \psi_{\mathrm{LP}}, \psi_{\mathrm{P}}, \psi_{\mathrm{LS}}, \psi_{\mathrm{S}}, \psi_{\mathrm{T}})$. The results of this exercise, assuming different values of α for each country, are reported in Table 6.

Table 6: Results (with varying α)

	NO	LP	P	LS	S	T
ψ_j	0.1622	0.1686	0.2136	0.1282	0.1919	0.1355
$\tilde{\rho}_j$	0.1051	0.1042	0.1045	0.1011	0.1047	0.1019

An aggregate "social return to schooling" from these calculations can be constructed as

$$\tilde{\rho} := \sum_{j=1}^{m} \phi_j \tilde{\rho}_j,$$

which yields an average of 0.108 for the entire sample, with a standard deviation of 0.054. This implies an excess return to schooling $(\tilde{\rho} - \rho)$ in the order of 1.2%, which we take as our lower-bound estimate for aggregate human-capital externalities, and complements the analysis of the previous section.

To conclude this section, we show that assuming a constant labor share across countries, as is common practice in this literature, tends to decrease social returns to schooling, hence the role

[5] The function conjectured for h_j could also have different values for the constant, say B_j, but this assumption is made to simplify the estimation method.

of human capital externalities on income per worker. For this, we repeat the previous exercise restricting $\alpha = 1/3$ for all countries, and summarize the results in Table 7 below.

Table 7: Results (with $\alpha = 1/3$)

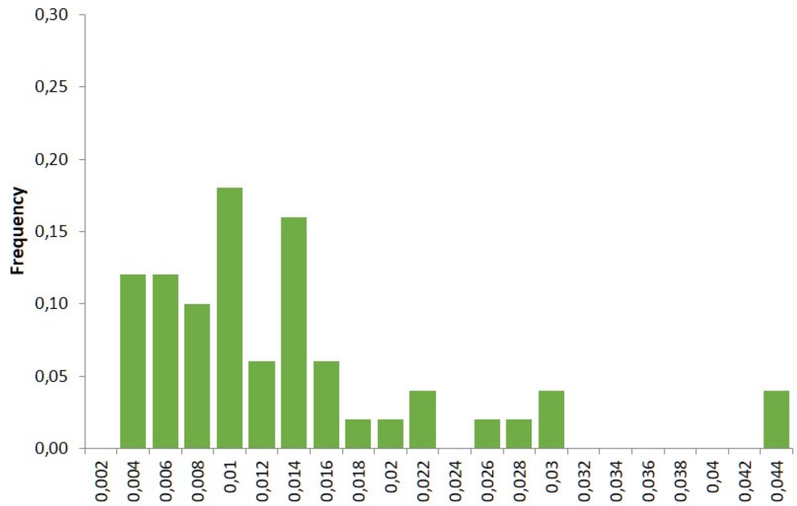
	NO	LP	P	LS	S	T
ψ_j	0.1645	0.1700	0.2148	0.1288	0.1880	0.1339
$\tilde{\rho}_j$	0.1021	0.1017	0.1025	0.0998	0.1020	0.1003

In this case, the average social return to schooling falls to 0.105 with a standard deviation of 0.052, which implies an excess return to schooling that is only 0.9%. The implied frequency distributions of excess returns to schooling for both cases are shown in Figure 3.

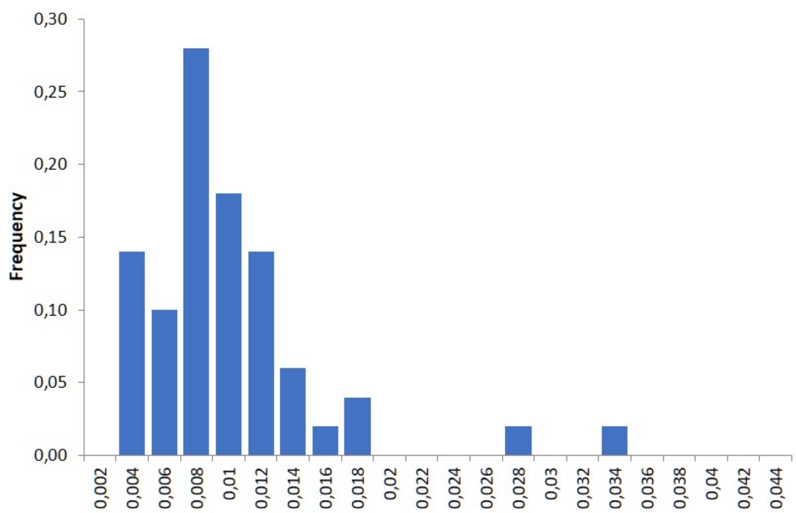
5 Conclusions

This paper proposes a method to identify and estimate aggregate human capital externalities in a model of heterogeneous agents that imposes consistency between micro-level and macro-level Mincer returns to schooling. Externalities are estimated to be in the order of 1-5%, which are in line with the most recent findings in the literature.

Figure 3: Excess returns to schooling



(a) with α varying across countries



(b) without α varying across countries

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