TESTING CAPITAL-SKILL COMPLEMENTARITY ACROSS SECTORS IN A PANEL OF SPANISH REGIONS*

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ABSTRACT

The aim of this paper is to examine the evidence for capital-skilled labor complementarity in six different activity sectors using aggregate production function specifications and a time-series, cross-section panel of Spanish regions. Estimation results have troubles finding evidence that supports departing from the Cobb-Douglas assumption and, if anything, find capital skill substitutablity in most sectors. They also suggest that capital skill complementarity might be a sector-specific phenomenon.

Keywords: Input complementarity, aggregate production function, panel data.

RESUMEN

El objetivo de este artículo es examinar la evidencia sobre la hipótesis capital-habilidad en seis diferentes sectores de actividades usando funciones de producción agregada en un panel de regiones españolas. Los resultados de la estimación tienen problemas para encontrar evidencia que apoye el separarse del supuesto Cobb-Douglas y, si acaso, encuentran substituibilidad entre el capital y la mano de obra cualificada en la mayoría de los sectores. También sugieren que la complementariedad capital-habilidad puede ser un fenómeno específico a ciertos sectores.

Palabras clave: Complementariedad de los *inputs*, funciones de producción agregada, datos de panel.

JEL: O40, O47.

1 Introduction

Over 30 years ago, Griliches (1969) provided evidence from U.S. manufacturing data suggesting that capital and skilled labor are relatively more complementary as inputs than are capital and unskilled labor. Griliches referred to this finding as the "capital–skill complementarity" hypothesis. Griliches' hypothesis has received renewed attention lately, as the U.S. and other developed nations have invested heavily in "skill–biased" information technology and this development appears to have coincided with a rise in the wages earned by skilled workers relative to the wages of unskilled workers. Indeed, belief in the existence of capital–skill complementarity is so strong that some researchers have suggested modifying the standard neoclassical production technology to account for this phenomenon in addressing questions of economic growth, trade and inequality (see, e.g. Stokey (1996), and Krusell et al. (2000)).

Since Griliches (1969), the capital–skill complementarity hypothesis has obtained empirical support in many instances from researchers that have mainly used cross–sectional manufacturing data. For example, Fallon and Layard (1975), Berman *et al.* (1998), Flug and Hercowitz (2000), and Duffy *at al.* (2004). However, Hamermesh (1993) assesses the findings from most of these studies and concludes that there "may be" capital–skill complementarity. However, he cautions that "many of the studies that disaggregate the work force by demographic group exclude capital as a productive input due to the difficulty of generating satisfactory data on capital stocks in the cross sections examined" (Hamermesh (1993) p. 113). For example, in the original Griliches (1969) study, the assumption of perfectly competitive markets allows data on rates of return to proxy for the marginal product of capital and thereby capture variations in the stock of capital. Hamermesh (1993) also notes the difficulties that earlier studies had in using occupational data to differentiate between skilled and unskilled workers.

In addition, as Goldin and Katz (1998) have recently reminded us, physical capital and skilled labor have not always been viewed as relative complements. For example, they note that in an earlier era, the transformation from skilled artisan shops to factories involved the substitution of physical capital and/or unskilled labor for highly skilled labor – precisely the opposite of what is hypothesized to be happening today. Goldin and Katz's findings suggest that capital–skill complementarity may only be a transitory and sector-specific phenomenon. Compared to unskilled labor, skilled labor may be more substitutable with capital in some sectors than in others. In addition, as sectors evolve, inputs may change their degree of complementarity. It therefore seems important to consider the evidence for capital–skill complementarity over long periods of time and across sectors.

The aim of this paper is to conduct such an exercise. I examine the evidence for capital–skill complementarity using a panel data set of Spanish regions. The sample is composed of 17 regions and six activity sectors over the period 1986–1998. We make use of available datasets on physical capital and human capital stocks. The focus is on Spain because this type of disaggregate data on capital stocks does not seem to be easily available in other nations. We examine the capital–skill complementarity hypothesis *directly*, without resorting to assumptions of perfectly competitive markets, by estimating the parameters of various different specifications of an aggregate production function.[1] In addition, we follow the tradition in the macro–growth literature and differentiate labor according to educational attainment levels. In particular, we consider four alternative proxies for skilled labor. For each proxy, the fraction of the labor force that does not meet the educational threshold used to define skilled labor is regarded as unskilled labor. The first one considers as skilled workers those possessing at least three years of tertiary education. The second one includes as skilled any worker with completed secondary education. The third and fourth ones are versions of the previous measures that augment our labor data with data on returns to schooling (earnings) in an effort to account for disparities in efficiency units across workers *within* the class of workers regarded as skilled or unskilled.

My approach is most closely related to the Fallon and Layard (1975) and Duffy *et al.* (2004) studies. Fallon and Layard used data pieced together for 9 developed and 13 less developed countries for a single year, 1963, to estimate reduced form equations derived from two–level CES production functions that allowed for differences in the elasticity of substitution between capital and skilled labor and the elasticity of substitution between capital and unskilled labor. At the economy–wide level, they find "mild" (though statistically insignificant) evidence in favor of the capital–skill complementarity hypothesis, but at the sectoral level they find strong evidence. Fallon and Layard, however, have neither capital stock data nor factor price data at the sectoral level. To deal with that, they assume perfectly competitive markets, and cross-sector equality of the efficiency parameter in each country so that marginal product conditions under perfect competition can be used to estimate linear reduced form equations. I, on the other hand, have access to capital stock data,

[1] The methodology used in this paper follows Duffy and Papageorgiou (2000) who investigate a general two–factor CES aggregate specification in which output is generated using physical capital and labor or human capital adjusted labor serving as inputs.

and can directly estimate the production function allowing differences in efficiency across sectors. Furthermore, there is also a time dimension to my panel dataset that was missing from Fallon and Layard's study, and many more sample points. Duffy *el al.* follow the same methodology than me, and find weak support to the hypothesis using an international panel with 73 nations and 16 years of data. Unlike them, I estimate the elasticity of input substitution at the sectoral level.

The main result of the paper is that panel data on Spanish regions have troubles finding evidence that supports departing from the Cobb-Douglas assumption and, if anything, supports capital skill substitutablity in most sectors.

2 Capital Skill Complementarity and Aggregate Production Functions

The capital–skill complementarity hypothesis states that physical capital is more complementary to skilled labor than to unskilled labor. More formally, suppose aggregate output, Y, is given by a three–factor production technology $Y = F(K, S, N)$, where K denotes the physical capital stock, S denotes the quantity of skilled labor and N denotes the quantity of unskilled labor. Denote by $\sigma_{i,j}$ the elasticity of substitution (ES) between inputs i and j.

Capital–skill complementarity holds if $\sigma_{K,N} > \sigma_{K,S} \Leftrightarrow \frac{\partial}{\partial K}\left(\frac{F_S}{F_N}\right) > 0$. To see that this is true, let us use the following definitions of the elasticity of substitution:

$$\begin{aligned} \sigma_{K,N} &= El_{R_{K,N}}(K/N) = \frac{R_{K,N}}{K/N}\frac{\partial(K/N)}{\partial(R_{K,N})}, \\ \sigma_{K,S} &= El_{R_{K,S}}(K/S) = \frac{R_{K,S}}{K/S}\frac{\partial(K/S)}{\partial(R_{K,S})}, \end{aligned}$$

where $El_x(z)$ denotes the elasticity of z with respect to x (the percentage change in z given a percentage change in x), $R_{i,j} = \frac{F_j}{F_i}$ is the Marginal Rate of Technical Substitution (MRTS) between inputs i and j. Starting from the inequality $\sigma_{K,N} > \sigma_{K,S}$ and manipulating the ES definitions we obtain that

$$\frac{\partial(F_S/F_K)}{\partial(K/S)}\frac{1}{SF_S} > \frac{\partial(F_N/F_K)}{\partial(K/N)}\frac{1}{NF_N}. \tag{1}$$

Finally, using the chain rule we show that $\frac{F_{S,K}}{F_S} > \frac{F_{N,K}}{F_N}$, where $F_{i,j}$ is the cross–partial derivative. It is then easily shown that

$$\frac{F_{S,K}}{F_S} > \frac{F_{N,K}}{F_N} \Leftrightarrow \frac{\partial}{\partial K}\left(\frac{F_S}{F_N}\right) > 0. \tag{2}$$

In order to assess the extent of capital skill complementarity, we must work with a functional form that is general enough to accommodate different elasticities of substitution. For example, the relatively general CES form for $F(K, S, N)$,

$$Y = A\left[aK^{\rho} + bS^{\rho} + cN^{\rho}\right]^{\frac{1}{\rho}}, \tag{3}$$

where $a+b+c = 1$ and $\rho \leq 1$, implies that the elasticity of substitution between any two inputs, $\sigma_{i,j}$ for $i, j \in \{K, S, N\}$, is constant and equal to $\frac{1}{1-\rho}$. To allow for different elasticities of substitution between any two inputs requires a two–level CES form á la Fallon and Layard (1975). For example,

$$Y = A\left[a[bK^{\theta} + (1-b)S^{\theta}]^{\rho/\theta} + (1-a)N^{\rho}\right]^{1/\rho}, \ \sigma_{K,S} = \frac{1}{1-\theta}, \sigma_{K,N} = \sigma_{N,S} = \frac{1}{1-\rho}, \tag{4}$$

where A is a positive technological parameter, a, b are distribution parameters and θ, $\rho \leq 1$ are the elasticity of substitution parameters (θ, $\rho = 1$ imply perfect substitutability, θ, $\rho = 0$ imply the Cobb–Douglas specification, and θ, $\rho = -\infty$ imply perfect complementarity). Recent literature examining the consequences of the capital–skill complementarity hypothesis that have used this specification include Krusell *et al.* (2000), Caselli and Coleman (2002), and Duffy *et al.* (2004).[2] The latter paper proves that the two–level CES technology of equation (4) implies that capital–skill complementarity hypothesis holds iff $\rho > \theta$.[3]

An alternative specification is suggested by Stokey (1996). She proposes a more restrictive form, a CES nested in a Cobb-Douglas specification:

$$Y = A[bK^{\theta} + (1-b)N^{\theta}]^{\gamma/\theta} S_q^{(1-\gamma)}. \tag{6}$$

[2]Krusell *et al.* consider an expanded version of specification (4)

$$Y = AK_s^{\alpha}\left[a[bK_e^{\theta} + (1-b)S^{\theta}]^{\rho/\theta} + (1-a)N^{\rho}\right]^{\frac{1-\alpha}{\rho}}, \tag{5}$$

where K_s represents the stock of capital structures, and K_e represents the stock of capital equipment. Further disaggregation is also possible through, for example, the use of a translog specification, like in Bergström and Panas (1992) and Ruiz–Arranz (2002).

[3]For general production technologies with more than two inputs there is no single definition for the elasticity of substitution between pairs of inputs. Perhaps the most commonly used definition is the Allen–Uzawa *partial* elasticity of substitution that measures the percentage change in the ratio of two inputs in response to a change in the ratio of the two input prices, holding all other prices (but not all other inputs) and output quantity constant. This is the measure used, e.g. by Griliches (1969). Another elasticity of substitution definition is the Hicks–Allen *direct partial* elasticity of substitution that measures the percentage change in the ratio of two inputs in response to a change in the ratio of the two input prices, holding all other prices, inputs and output quantity constant. Duffy *et al.* (2004) show that, in the two–level CES specification (4), the capital–skill complementarity hypothesis ($\sigma_{K,N} > \sigma_{K,S}$) holds iff $\rho > \theta$ regardless of which elasticity measure you use, the Allen partial elasticity of substitution or the direct partial elasticity of substitution.

Here $S_q = S + qN$ represents "mental effort", $q < 1$ is the relative efficiency of unskilled labor in contributing to mental effort, and $1-\gamma$ is the share of output that accrues to S_q. Compared to the two-level CES technology, the CES-in-CD formulation imposes a value of zero for the parameter ρ. The CES-in-CD version of specification (4) is then:

$$Y = A[bK^\theta + (1-b)S^\theta]^{\gamma/\theta} N^{1-\gamma}, \tag{7}$$

In formulations (6) and (7), capital–skill complementarity holds if $0 < \theta \leq 1$ and $\theta < 0$, respectively.[4]

Even though specifications (6) and (7) are very similar, they differ in one important way. Notice that where (7) implies that the elasticity of substitution between K and N, and N and S are the same (i.e. $\sigma_{K,N} = \sigma_{N,S}$), equation (6) implies that the elasticity of substitution between K and S, and N and S are the same (i.e. $\sigma_{K,S} = \sigma_{N,S}$).

Goldin and Katz (1998) start off with the two–level CES specification (4) but further specialize it to the case where 1) $\theta \to -\infty$ and 2) $\rho \to 0$. This is even more restrictive than Stokey (1996), since it implies, as in Stokey, that final output Y has the Cobb–Douglas form but it further requires that the K–S aggregate, which Goldin and Katz refer to as K^*, have the Leontief form:

$$Y = A\left[(\min[bK, (1-b)S])^\gamma N^{1-\gamma}\right]. \tag{8}$$

In this case, since $\sigma_{K,S} = 0 < 1$ and $\sigma_{K^*,N} = 1$, the authors are making the empirically testable assumption that $\sigma_{K,S} < \sigma_{K^*,N}$. Their aim is to show that if technology changes, represented by a change in A, then it need not be the case that the relative demand for skilled labor increases. As A increases, less is needed of both the K^* aggregate and N to produce the same level of output.

3 Estimation Procedures and Specifications

The two–level CES specification is highly nonlinear and can not be linearized. Therefore, nonlinear estimation methods are needed to obtain estimates of ρ and θ in specification (4). However, as Duffy *et al.* (2004) show the precision of non-linear estimation of the elasticity of substitution is relatively low. The CES-in-CD version, on the other hand, can be approximated linearly. Given this, I decide performing our estimation effort using a linear approximation of the CES-in-CD formulation. The estimation methodology used is GMM.

[4]See Duffy *et al.* (2204).

My CES-in-CD formulation is a version of Stokey's production function, and has the following form:

$$Y_{it} = A_{i0}[bK_{it}^{\theta} + (1-b)N_{it}^{\theta}]^{\gamma/\theta} S_{it}^{1-\gamma} e^{\lambda t + \varepsilon_{it}}, \tag{9}$$

where i and t represent region i and year t, respectively. In (9), capital and unskilled workers are combined into an aggregate by a CES specification. The resulting aggregate measure is then combined with skilled labor using a Cobb–Douglas technology. Notice that specification (9) is really a special case of (6) in that we assume that $q = 0$; this assumption implies that mental effort in the production process is exerted only by skilled workers.[5] The capital–skill complementarity would hold in this case if the elasticity of substitution between capital and unskilled workers is greater than unity, that is, $0 < \theta \leq 1$. Similarly, the restricted version of specification (4) that we will estimate is given by

$$Y_{it} = A_{i0}[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]^{\gamma/\theta} N_{it}^{1-\gamma} e^{\lambda t + \varepsilon_{it}}, \tag{10}$$

where the sufficient condition for capital–skill complementarity is reversed, $\theta < 0$.

It is possible to obtain a linearized version of the CES–in–CD specification as follows. First, divide the left and right hand sides of (9) by S_{it}, and the left and right hand sides of (10) by N_{it}. Then, log–linearize the resulting equations around $\theta = 0$ using a second order Taylor expansion to get, respectively,

$$\log y_{it} = \log A_{i0} + \lambda t + \gamma b \log k_{it} + \gamma(1-b)\log n_{it} + 1/2\gamma b(1-b)\theta \left(\log \frac{k_{it}}{n_{it}}\right)^2 + \varepsilon_{it}, \tag{11}$$

where $y = \frac{Y}{S}$, $k = \frac{K}{S}$, $n = \frac{N}{S}$, and

$$\log y_{it} = \log A_{i0} + \lambda t + \gamma b \log k_{it} + \gamma(1-b)\log s_{it} + 1/2\gamma b(1-b)\theta \left(\log \frac{k_{it}}{s_{it}}\right)^2 + \varepsilon_{it}, \tag{12}$$

where $y = \frac{Y}{N}$, $k = \frac{K}{N}$, $s = \frac{S}{N}$.

I also consider their differentiated version to get rid off country–specific fixed effects. In particular, log–differencing (11) and (12), we obtain the following two expressions:

$$\log \frac{y_{it}}{y_{it-1}} = \lambda + \gamma b \log \frac{k_{it}}{k_{it-1}} + \gamma(1-b)\log \frac{n_{it}}{n_{it-1}} + 1/2\gamma b(1-b)\theta \left[\left(\log \frac{k_{it}}{n_{it}}\right)^2 - \left(\log \frac{k_{it-1}}{n_{it-1}}\right)^2\right] + u_{it}, \tag{13}$$

[5] There exists no empirical evidence on q (the contribution of unskilled labor to mental effort). Stokey (1996) simply assumes that $q = 0.25$ in order to keep the skill premium within a reasonable range in her calibration exercises.

and

$$\log\frac{y_{it}}{y_{it-1}} = \lambda + \gamma b \log\frac{k_{it}}{k_{it-1}} + \gamma(1-b)\log\frac{s_{it}}{s_{it-1}} + 1/2\gamma b(1-b)\theta\left[\left(\log\frac{k_{it}}{s_{it}}\right)^2 - \left(\log\frac{k_{it-1}}{s_{it-1}}\right)^2\right] + u_{it}. \tag{14}$$

I will estimate expressions (11) to (14) using OLS, and the GMM procedure where lagged values of input and output variables will be employed as instruments.[6] This methodology was initially imported into the growth literature by Caselli et al. (1996) and has subsequently become an important benchmark estimation method.[7]

4 The Data

Our estimation requires data for real GDP (Y), the stock of physical capital (K), unskilled labor (N), and skilled labor (S). We obtain data for Y from the Spanish Institute of Statistics (INE), for K from the FBBVA-IVIE dataset, and for years of education of the labor force from the Bancaja-IVIE dataset. Data for Y corresponds to the real gross value added at input prices (1995 constant prices). The variable K is the gross physical capital stock measured in year-2000 constant prices. Data on schooling divide the Spanish labor force in five different categories: (1) illiterate, (2) primary education, (3) completed secondary education, (4) three-years completed of tertiary education, (5) at least five years completed of tertiary education.

With this information, I construct four alternative proxies for skilled (unskilled) labor because it is not clear how skilled labor should be defined. The first one, called it S_{1U}, includes categories (4) and (5) as skilled workers, that is, those with at least three years of tertiary education. The second one, S_{2U}, considers (3), (4) and (5) as the skilled labor force, and represents the labor force with at least completed secondary education. Measures three (S_{1W}) and four (S_{2W}) follow Caselli and Coleman (2002a) and employ additional data on returns to schooling to weight individuals *within* our two divisions of the labor force (skilled and unskilled). The reason is that, for example, workers

[6] In particular, GMM estimation of (11) and (13) uses $\log y_{i,t-2}$, $\log y_{i,t-3}$, $\log k_{i,t-2}$, $\log k_{i,t-3}$, $\log n_{i,t-2}$, $\log n_{i,t-3}$, $(\log(k_{it-2}/n_{it-2}))^2$ and $(\log(k_{it-3}/n_{it-3}))^2$ as instruments. For expressions (12) and (14), $\log s_{i,t-2}$, $\log s_{i,t-3}$, $(\log(k_{it-2}/s_{it-2}))^2$ and $(\log(k_{it-3}/s_{it-3}))^2$ substitute the last four instruments.

[7] Blundell and Bond (1998, 2000) suggest an alternative approach that involves GMM estimation of a *system* of production functions in both levels and first differences using lagged first differences of all variables dated $t-2$ and earlier as instruments in the levels equation and lagged levels dated $t-3$ and earlier as instruments in the first difference equation. They find that this alternative "systems approach" yields lower standard errors as compared with the GMM first–difference estimator of Arellano and Bond (1991) when applied to linear models. It is unclear whether the benefits of the systems estimator would extend to the nonlinear production function specification that I estimate. Furthermore, applying this approach would come at the cost of reducing the number of observations we have available. I leave such an exercise to future research.

who have attained some college education may contribute more efficiency units than workers who have only attained some secondary education. As a consequence, the proxies we used for skilled and unskilled labor could suffer from aggregation problems. Educational thresholds for S_{1W} and S_{2W} are the same as for S_{1U} and S_{2U}, respectively. The remainder of the labor force, those not classified under S_{1U}, S_{2U}, S_{1W} or S_{2W}, is regarded as unskilled labor and designated by N_{1U}, N_{2U}, N_{1W} and N_{2W}, corresponding to the definition of skilled labor. Other possible definitions were not considered in the paper because categories (1) and (5) contain zeros for some regions.

We have data on 6 different 1-digit sectors: agriculture and fishery, energy products, industrial products, construction, services for sale, and services not for sale. For each sector, our balanced panel dataset consists of 17 Spanish regions with 13 annual observations of all input and output variables starting in 1986 and ending in 1998. This, in principle, allows for 221 sample points for sector. However, GMM estimation employs three lags of dependent and independent variables as instruments. Hence, the final sample for each sector is composed of 170 observations.[8]

The data appendix provides further details concerning the sources and construction of the data used in this paper.

5 Results

We report estimation results for the specifications (9) and (10), using the various estimation techniques: without and with fixed effects removed (with FE) and using instrumental variable (IV) estimators. Numbers are in Tables 1 to 6 at the end of the paper.

The first thing that I want to notice is that, in general, estimation does not show clearly that specification (10) is strongly preferred to (9) as most previous work such as Fallon and Layard (1975), Krusell et al. (2000) and Duffy *at al.* (2004), argues. Implausible values of the parameters are found sometimes in both specifications, like parameter estimates that had the wrong signs, had very large standard errors, or are empirically implausible in magnitude, e.g. estimates for θ in excess of one. What I do find is that the numbers of times that expression (9) produces implausible values is larger, but the difference does not seen to be overwhelming. For that reason, I report results from both specifications.

Recall that capital skill complemetarity holds in (9) when $\theta \in (0, 1)$, and in (10) when $\theta < 0$. We

[8]An exception is the energy products sector for which we have only 16 regions. La Rioja was dropped from the sample due to the existence of zeros.

see in that significant estimated values of θ in agriculture and fishery (Table 1), energy products (Table 2), industry (Table 3), and construction (Table 4) support many more times the case of capital skill substitutability. On the contrary, significant estimated values support more times the case of capital skill complementary in the sevices not for sale sector (Table 6). Finally, in the services for sale sector (Table 5), the number of times in favor of capital skill complementarity and in favor of capital skill substitutability are very similar, in particular, 8 and 9 respectively.

Notice as well that, in most cases, estimates of the parameter θ are close to zero and not significant, whereas estimates of γ are most of the time significant. This makes clear the difficulty of finding evidence that supports departing from the Cobb-Douglas formulation.

Regarding the best measure of human capital, we find ambiguous results that depend on the production function specification. The goodness of fit (see R^2 with OLS) and the goodness of the instruments (see J-statistic with GMM) is generally larger with S_{1U} and S_{1W} in formulation (9), but with S_{2U} and S_{2W} in formulation (10). Comparing the weighted and unweighted measures, we see that they give very similar results in most cases, and neither one seems to be clearly preferred.

6 Conclusions

The aim of this paper has been to examine the evidence for capital–skilled labor complementarity in six different activity sectors using aggregate production function specifications and a time–series, cross–section panel of Spanish regions. We conclude that there is evidence in support of the capital–skill complementarity hypothesis only in the service not for sale sector. For agriculture and fishery, construction, energy products, and industrial products, we find evidence of capital skill substitutability. The paper points out that capital skill complementarity is a sector-specific phenomenon and not an economy-wide one. The paper has also implications for the debate concerning the source of rising wage and income inequality across countries. Some authors, e.g. Krusell et al. (2000) have pointed to capital–skill complementarity as the likely source of this phenomenon. Our lack of evidence for capital–skill complementarity in most sectors suggests that researchers might want to consider alternative, complementary explanations for rising inequality, for example, skill–biased technical change.

These results are in sharp contrast to the ones obtained by previous literature. Most researchers focusing on the manufacturing, Mining, Construction, and energy products such as Fallon and

Layard (1975) find support for capital skill complementarity. I, on the other hand, have troubles finding evidence that supports departing from the Cobb-Douglas assumption and, if anything, find capital skill substitutablity in these sectors.

Still, I urge caution in taking these results too seriously. There are many caveats. The CES nested in Cobb-Douglas specification is certainly not the most appropriate way to test the hypothesis. Trying a CES nested in CES formulation, as previous literature has done, may bring new light on the issue. In addition, as Krusell et al. (2000) has shown for the US economy, separating equipment capital from other forms of physical capital may be key to find capital skill complementarity. These are issues that must be addressed by future research.

Table 1: CES–in–CD, Linear Estimation, Agriculture and Fishery

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	0.034	0.026***	0.059	0.126***	θ	0.051	0.011***	−0.101	0.105**
	(0.049)	(0.012)	(0.051)	(0.031)		(0.100)	(0.003)	(0.099)	(0.045)
γ	0.927***	0.748***	1.016***	0.955***	γ	0.876***	0.724***	0.978***	0.795***
	(0.067)	(0.135)	(0.017)	(0.070)		(0.042)	(0.123)	(0.043)	(0.073)
R^2	0.914	0.702	0.953	0.554	J-st	8.475	12.708	7.557	9.209
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	0.056	0.051	0.053	0.044***	θ	0.056	0.138	−0.057	0.020***
	(0.147)	(0.110)	(0.046)	(0.016)		(0.061)	(0.667)	(0.036)	(0.008)
γ	0.802***	0.917***	0.911***	1.039***	γ	0.883***	0.983***	0.903***	0.917***
	(0.145)	(0.163)	(0.061)	(0.066)		(0.090)	(0.122)	(0.159)	(0.118)
R^2	0.543	0.754	0.625	0.598	J-st	10.172	9.781	6.297	7.459
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	0.026	0.026**	0.055	0.123***	θ	0.029	0.011***	−0.147	0.098**
	(0.031)	(0.0122)	(0.042)	(0.029)		(0.036)	(0.004)	(0.203)	(0.048)
γ	0.930***	0.743***	1.016***	0.952***	γ	0.878***	0.709***	0.976***	0.782***
	(0.066)	(0.142)	(0.017)	(0.070)		(0.042)	(0.137)	(0.043)	(0.080)
R^2	0.915	0.675	0.953	0.555	J-st	8.724	12.750	8.036	8.924
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	0.037	0.035***	0.059	0.056**	θ	0.038	0.059*	−0.068	0.026**
	(0.050)	(0.016)	(0.049)	(0.024)		(0.022)	(0.035)	(0.043)	(0.011)
γ	0.820***	0.924***	0.917***	1.039***	γ	0.881***	1.005***	0.914***	0.900***
	(0.142)	(0.161)	(0.058)	(0.062)		(0.081)	(0.118)	(0.144)	(0.098)
R^2	0.578	0.752	0.627	0.601	J-st	10.908	9.863	6.684	8.144

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Table 2: CES–in–CD, Linear Estimation, Energy Products

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	-0.021	2.501	0.060***	0.067	θ	-0.017*	-0.027	0.138	0.049*
	(0.016)	(144)	(0.023)	(0.048)		(0.009)	(0.043)	(0.502)	(0.026)
γ	0.934***	0.800***	0.997***	0.988***	γ	0.935***	0.600***	0.880***	1.024***
	(0.049)	(0.065)	(0.007)	(0.014)		(0.046)	(0.096)	(0.060)	(0.022)
R^2	0.874	0.780	0.979	0.918	J-st	12.835	10.127	12.330	10.799
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	-0.019**	-0.084	0.048***	0.052***	θ	-0.011***	-0.054	0.089***	0.017***
	(0.009)	(0.234)	(0.012)	(0.019)		(0.003)	(0.084)	(0.023)	(0.006)
γ	0.907***	0.901***	0.987***	0.985***	γ	0.809***	0.777***	0.956***	1.002***
	(0.056)	(0.064)	(0.012)	(0.015)		(0.052)	(0.091)	(0.025)	(0.023)
R^2	0.800	0.866	0.926	0.957	J-st	10.687	11.185	11.658	10.884
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	-0.027	-1.441	0.067***	0.064**	θ	-0.026	-0.029	0.025	0.072
	(0.024)	(51)	(0.024)	(0.033)		(0.016)	(0.041)	(0.026)	(0.081)
γ	0.939***	0.798***	0.997***	0.989***	γ	0.962***	0.603***	0.899***	1.026***
	(0.050)	(0.065)	(0.007)	(0.014)		(0.049)	(0.082)	(0.069)	(0.022)
R^2	0.876	0.774	0.979	0.919	J-st	12.536	10.311	10.957	10.013
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	-0.020**	-0.079	0.050***	0.050***	θ	-0.083***	-0.060	0.096*	0.017***
	(0.010)	(0.209)	(0.012)	(0.020)		(0.004)	(0.090)	(0.050)	(0.006)
γ	0.908***	0.891***	0.986***	0.985***	γ	0.893***	0.756***	0.946***	1.007***
	(0.054)	(0.063)	(0.013)	(0.015)		(0.045)	(0.081)	(0.025)	(0.023)
R^2	0.805	0.867	0.925	0.957	J-st	10.882	11.392	11.805	10.905

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Table 3: CES–in–CD, Linear Estimation, Industrial Products

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	0.013	0.806	0.074	0.240	θ	0.018	0.006***	0.022*	−0.011
	(0.008)	(50)	(0.069)	(0.644)		(0.013)	(0.002)	(0.012)	(0.016)
γ	0.767***	0.692***	0.991***	0.749***	γ	0.697***	0.714***	1.121***	0.431**
	(0.034)	(0.091)	(0.013)	(0.073)		(0.033)	(0.046)	(0.066)	(0.206)
R^2	0.834	0.821	0.953	0.552	$J\text{-}st$	13.307	8.660	7.170	11.534
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	0.007	0.012***	0.311	0.021***	θ	0.002	0.010***	−0.120	0.021***
	(0.017)	(0.002)	(1.172)	(0.003)		(0.013)	(0.001)	(0.304)	(0.006)
γ	0.266**	1.319***	0.846***	0.864***	γ	0.068	1.450***	0.754***	1.064***
	(0.126)	(0.135)	(0.048)	(0.033)		(0.088)	(0.112)	(0.090)	(0.095)
R^2	0.655	0.934	0.709	0.690	$J\text{-}st$	9.585	11.348	13.375	11.602
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	0.014**	−0.990	0.057*	0.193	θ	0.019	0.006***	0.013***	−0.011
	(0.)	(70)	(0.033)	(0.338)		(0.012)	(0.002)	(0.004)	(0.012)
γ	0.779***	0.682***	0.994***	0.750***	γ	0.698***	0.712***	1.118***	0.419***
	(0.035)	(0.090)	(0.013)	(0.073)		(0.034)	(0.047)	(0.066)	(0.196)
R^2	0.848	0.804	0.955	0.565	$J\text{-}st$	12.520	8.300	4.745	11.352
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	0.008	0.012***	0.316	0.023***	θ	0.044	0.009***	−0.122	0.022***
	(0.020)	(0.002)	(1.114)	(0.004)		(0.016)	(0.001)	(0.257)	(0.007)
γ	0.294***	1.277***	0.853***	0.862***	γ	0.164*	1.367***	0.790***	1.028***
	(0.111)	(0.122)	(0.044)	(0.033)		(0.095)	(0.092)	(0.090)	(0.090)
R^2	0.625	0.934	0.719	0.686	$J\text{-}st$	10.444	12.307	13.654	11.439

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Table 4: CES–in–CD, Linear Estimation, Construction

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	0.090	0.029	-0.091	0.050***	θ	0.045	0.009	0.009	-0.056
	(1.656)	(0.042)	(0.133)	(0.106)		(0.087)	(0.014)	(0.009)	(0.290)
γ	0.874***	0.556***	0.971***	0.493***	γ	0.782***	0.465***	1.017***	0.332***
	(0.037)	(0.054)	(0.013)	(0.070)		(0.056)	(0.061)	(0.039)	(0.118)
R^2	0.953	0.781	0.945	0.297	$J\text{-}st$	14.055	14.253	14.294	14.664
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	0.678	0.020	1.173	0.012***	θ	0.101	0.015*	0.006	-0.037
	(12.905)	(0.015)	(31)	(0.004)		(0.226)	(0.009)	(0.009)	(0.051)
γ	0.695***	0.837***	0.688***	0.750***	γ	0.796***	0.866***	0.411***	1.271***
	(0.084)	(0.073)	(0.038)	(0.056)		(0.072)	(0.074)	(0.109)	(0.274)
R^2	0.666	0.904	0.503	0.557	$J\text{-}st$	11.562	12.328	9.950	10.486
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	-0.455	0.026	-0.095	0.053	θ	0.026	0.009	0.014	-0.024
	(12.66)	(0.039)	(0.154)	(0.110)		(0.032)	(0.014)	(0.021)	(0.190)
γ	0.881***	0.547***	0.967***	0.501***	γ	0.808***	0.483***	0.994***	0.200
	(0.040)	(0.062)	(0.012)	(0.066)		(0.058)	(0.067)	(0.040)	(0.137)
R^2	0.952	0.736	0.944	0.307	$J\text{-}st$	13.686	14.428	15.021	14.644
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	1.060	0.017	-0.709	0.012***	θ	0.126	0.011*	0.009	-0.033
	(30)	(0.013)	(9.486)	(0.004)		(0.378)	(0.006)	(0.012)	(0.034)
γ	0.675***	0.827***	0.685***	0.764***	γ	0.778***	0.846***	0.464***	1.285***
	(0.089)	(0.068)	(0.039)	(0.056)		(0.072)	(0.068)	(0.096)	(0.253)
R^2	0.659	0.907	0.494	0.556	$J\text{-}st$	12.306	12.895	10.576	11.403

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Table 5: CES–in–CD, Linear Estimation, Services for Sale

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	-0.009	-0.021	0.026	0.035**	θ	-0.012	-0.029	0.012	0.005***
	(0.012)	(0.024)	(0.024)	(0.018)		(0.017)	(0.035)	(0.124)	(0.000)
γ	0.790***	0.801***	1.038***	0.973***	γ	0.753***	0.806***	1.335***	1.508***
	(0.046)	(0.094)	(0.035)	(0.090)		(0.023)	(0.059)	(0.122)	(0.373)
R^2	0.887	0.841	0.876	0.470	J-st	15.516	14.963	10.590	8.503
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	0.035	-0.015*	0.011***	0.006***	θ	12.277	-0.009***	0.007***	0.002***
	(0.258)	(0.009)	(0.003)	(0.003)		(13262)	(0.)	(0.)	(0.000)
γ	0.460***	1.085***	0.915***	0.963***	γ	0.385***	1.099***	1.017***	0.852***
	(0.072)	(0.039)	(0.077)	(0.036)		(0.072)	(0.034)	(0.225)	(0.072)
R^2	0.507	0.963	0.536	0.780	J-st	14.901	14.726	14.322	13.735
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	-0.007	-0.020	-0.114	0.038*	θ	-0.006	-0.026	0.014***	0.005***
	(0.007)	(0.022)	(0.648)	(0.020)		(0.006)	(0.028)	(0.003)	(0.001)
γ	0.802***	0.765***	1.033***	0.962***	γ	0.758***	0.771***	1.257***	1.767***
	(0.043)	(0.100)	(0.033)	(0.100)		(0.020)	(0.058)	(0.123)	(0.500)
R^2	0.896	0.805	0.878	0.444	J-st	15.782	14.883	10.757	7.687
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	0.040	-0.018	0.013***	0.008**	θ	0.038	-0.013*	0.009***	0.002***
	(0.204)	(0.014)	(0.003)	(0.003)		(0.254)	(0.007)	(0.001)	(0.001)
γ	0.512***	1.047***	0.957***	0.969***	γ	0.949***	1.053***	1.316***	0.858***
	(0.068)	(0.043)	(0.067)	(0.037)		(0.070)	(0.031)	(0.238)	(0.055)
R^2	0.546	0.961	0.575	0.777	J-st	15.068	15.135	13.130	14.197

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Table 6: CES–in–CD, Linear Estimation, Services Not for Sale

	OLS		OLS-FE			GMM		GMM-FE	
S_{1U}	S out	N out	S out	N out	S_{1U}	S out	N out	S out	N out
θ	-0.023	-0.008	0.024***	0.143	θ	0.026	0.002	-0.114	0.022***
	(0.023)	(0.029)	(0.010)	(0.029)		(0.039)	(0.007)	(0.393)	(0.002)
γ	0.794***	0.386***	1.051***	0.969***	γ	0.575***	0.223*	0.977***	1.523***
	(0.106)	(0.106)	(0.030)	(0.029)		(0.137)	(0.130)	(0.127)	(0.112)
R^2	0.673	0.728	0.866	0.789	J-st	11.580	11.811	11.753	10.926
S_{2U}	S out	N out	S out	N out	S_{2U}	S out	N out	S out	N out
θ	0.040***	-0.017	0.022***	0.136	θ	-0.002	0.021	0.019***	-0.160
	(0.007)	(0.038)	(0.004)	(0.235)		(0.010)	(0.016)	(0.001)	(0.506)
γ	0.143**	0.886***	1.009***	0.984***	γ	-0.108**	0.954***	1.304***	1.114***
	(0.069)	(0.077)	(0.038)	(0.021)		(0.054)	(0.056)	(0.079)	(0.041)
R^2	0.451	0.931	0.791	0.895	J-st	13.149	13.250	7.697	12.126
S_{1W}	S out	N out	S out	N out	S_{1W}	S out	N out	S out	N out
θ	-0.026	-0.011	0.032**	0.146	θ	0.031	0.001	-0.023	0.021***
	(0.026)	(0.049)	(0.014)	(0.183)		(0.036)	(0.006)	(0.030)	(0.002)
γ	0.814***	0.365***	1.052***	0.965***	γ	0.677***	0.137	0.932***	1.586***
	(0.095)	(0.101)	(0.030)	(0.030)		(0.119)	(0.114)	(0.172)	(0.129)
R^2	0.690	0.695	0.865	0.787	J-st	12.021	11.813	11.107	10.999
S_{2W}	S out	N out	S out	N out	S_{2W}	S out	N out	S out	N out
θ	0.008	-0.016	0.023***	0.150	θ	-0.001	0.022	0.019***	-0.360
	(0.040)	(0.015)	(0.004)	(0.258)		(0.010)	(0.020)	(0.001)	(2.050)
γ	0.199***	0.835***	1.025***	0.985***	γ	-0.065	0.903***	1.270***	1.105***
	(0.067)	(0.088)	(0.040)	(0.020)		(0.053)	(0.066)	(0.077)	(0.032)
R^2	0.455	0.923	0.813	0.896	J-st	12.077	12.146	8.874	12.933

Notes: Heteroskedasticity- and autocorrelation-corrected standard errors, in parentheses, were recovered using standard approximation methods. ***, **, * Significantly different from 0 at the 1% , 5%, and 10% levels, respectively.

Data Appendix

- *Income (Y)* [Source: INE]

Gross Value Added (GVA) at constant prices per region and sector from 1986 to 1995, GVA at basic prices from 1996 to 1998. Constant prices of 1986. Available on–line at: http://www.ine.es/.

- *Physical capital stocks (K)* [Source: FBBVA-IVIE]

Net capital stocks, 1986 constant prices, from the "Stock de Capital en España y su distribución territorial (1964-2000)" dataset. Available on–line at:
http://w3.grupobbva.com/TLFB/tlfb/TLFBindex_pub.jsp.

- *Skilled and Unskilled Labor (S, N)* [Source: Bancaja-IVIE]

Data on people in employment by provinces and Autonomous Regions in the following categories: illiterate, no formal education or primary education, completed compulsory secondary education, completed pre-university education, completed higher education. Data is available at:
http://www.ivie.es/banco/capital.php?idioma=EN.

From these data, we construct two alternative proxies for skilled and unskilled labor as follows:

Unweighted data

1. S_{1U} is equal to the number of workers with completed pre-university education or completed higher education; N_{1U} is equal to the rest of the workers in the sector.

2. S_{2U} is equal to the number of workers with completed compulsory secondary education or completed pre-university education or completed higher education; N_{2U} is equal to the rest of the workers in the sector.

Weighted data

To obtain the other two measures (S_{1W}, N_{1W} and S_{2W}, N_{2W}), we weigh individuals within a given skill class, S_{iU} and N_{iU}, i = 1,2, by a function of the length in years of their schooling level times the return to schooling. In addition, the aggregate value is constructed so that it is measured in terms of the efficiency units of the lowest educational subcategory included in the skill class. A return to schooling in Spain of 8.36% is taken from Alba-Ramirez y San Segundo (1995), and were obtained following the Mincerian approach which assumes that log–wages are linear in years of schooling. We assume that, compared to its previous schooling category, no formal education or primary education ($nfepe$) represent, on average, 6 years of additional education, completed compulsory secondary education ($ccse$) represents 4 additional years, completed pre-university education ($cpue$) implies 5 more years, and completed higher education (che) implies 2 years of additional schooling.

An example: Let $L_{j,ik}$ the number of workers of educational level j in sector i and region k. For sector i and region k, S_{2W} and N_{2W} are computed as follows:

$$\begin{aligned} S_{2W}(i,k) &= L_{ccse,jk} + \exp(0.0836 * 5)\, L_{cpue,jk} + \exp[0.0836(5+2)] L_{che,jk}, \\ N_{2W}(i,k) &= L_{ill,jk} + \exp(0.0836 * 6)\, L_{nfepe,jk} \end{aligned}$$

where *ill* stands for illiterate.

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