The elasticity of substitution and labor-saving innovations in the Spanish regions*

La elasticidad de sustitución y las innovaciones ahorradoras de trabajo en las regiones españolas

Antonio Cutanda**

Abstract

This paper performs a nonlinear estimation of a normalized CES production function within a system of equations with a panel of Spanish regions for the period 1964-2013. It obtains an elasticity of substitution below one and identifies different rates of factor-augmenting technical progress. The results support for labor-saving innovations hypothesis for the Spanish case. Nevertheless, they do not support a relationship between the elasticity of substitution and the initial regional capital per worker. The results do not change if labor is adjusted by human capital.

Key words: *Production function, CES, normalization, regional data.*

JEL Codes: *C33, E23, O47.*

Resumen

En este trabajo se estima no linealmente una función de producción CES normalizada en el seno de un sistema de ecuaciones con datos de panel de las regiones españolas, para el período 1964-2013. Se obtiene una elasticidad de sustitución menor que uno y se identifican diferentes tasas de progreso técnico aumentativo de la eficiencia de los factores productivos. Los resultados obtenidos sustentan la hipótesis de innovaciones ahorradoras de trabajo para el caso español. Sin

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** Departamento de Análisis Económico. Facultad de Economía. Universidad de Valencia. 46022 - Valencia (Spain). E-mail: antonio.cutanda@uv.es.

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embargo, no dan apoyo a la existencia de una relación entre la elasticidad de sustitución y el capital regional inicial por trabajador. Los resultados no cambian cuando se ajustan los datos del trabajo por capital humano.

Palabras clave: *Función de producción, CES, normalización, datos regionales.*

Códigos JEL: *C33, E23, O47.*

1. Introduction

For much of the 20th century, the stability of factor income shares has been considered a stylized fact of macroeconomic empirical analysis. Nevertheless, despite important measurement problems, there is now robust evidence of a decline in the labor income share.[1] Karabarbounis and Neiman (2014) explain the decline in the US by the fall in the relative price of investment goods, although Lawrence (2015) criticizes this explanation for assuming an elasticity of substitution greater than one along with Hicks-neutral technical progress. He argues that the decline can be better explained by an elasticity lower than one, a claim that is supported by US empirical evidence.[2]

The estimation of the Constant Elasticity of Substitution (CES) production function has traditionally been a very complex task, not least due to the *identification issue*. On the one hand, the *impossibility theorem* proposed by Diamond *et al*. (1978) states that it is not feasible to simultaneously identify the elasticity of substitution and biased technical change with a CES production function. On the other, the empirical research has not reached a clear consensus on the value of the elasticity, although it seems to agree that it is below one for the US economy (Chirinko, 2008; Young, 2013; Chirinko and Mallick, 2020; Gechert *et al*., 2021; Knoblach, Rößler and Zwerschke, 2020; Knoblach and Stöckl, 2020).

However, the normalization procedure, developed by De La Grandville (1989) and Klump and De La Grandville (2000), has further raised the interest in the estimation of the CES production function. According to Klump *et al*. (2007), it resolves the identification problem, especially when the CES function is estimated within a system of equations that includes the first-order conditions of profit maximization. In this study, it is applied this procedure to run a nonlinear estimation of a CES production function with Spanish regional data, although unlike Klump *et al*. (2007) I do not first log linearize it, to avoid the approximation bias. I check for the effect of human capital and heterogeneity, as well as biased technical change, as this approach allows to simultaneously

[1] See, for example, Rodriguez and Jayadev (2010).

[2] Recently, Glover and Short (2020) criticize Karabarbounis and Neiman (2014) for not having considered the effect of consumption in their analysis.

identify the elasticity of substitution and the rates of factor-augmenting technical progress. Finally, I apply a fixed-effects approach to our panel of regional data. In this sense, the application of panel data techniques to the estimation of the production function enjoys more degrees of freedom and can yield more efficient estimates. To my knowledge, this is the first estimation of a CES production function within a system of equations with Spanish regional data.

In contrast to previous studies, the results allow to conclude that the Spanish elasticity of substitution is below one, as in the US and other developed countries. I find that the *impossibility theorem* holds when the CES function is estimated as a single equation, the most used estimation method in previous empirical analysis for the Spanish economy, but not when it is estimated within a system of equations. Similar to Villacorta (2017), but unlike Dorazelski and Jaumandreu (2016), I obtain a negative estimate of the growth rate of labor-augmenting technical progress for the Spanish economy. In fact, the results can be taken as evidence of labor-saving (Boldrin and Levine 2002; Zuleta 2008) or labor-eliminating technical progress (Seater, 2005; Peretto and Seater, 2013). Finally, they also reject the existence of a relationship between the elasticity of substitution and the initial capital per worker.

The study is organized as follows: section 2 presents the theoretical model while section 3 describes the data; in section 4 the results are presented and commented, and section 5 concludes.

2. A CES Production Function for the Spanish Regions

Following Klump *et al*. (2007), we consider a linear homogeneous CES regional production function with technical change augmenting the efficiency of both inputs, capital and labor. For region *i*:

(1)
$$Y_{it} = C\left[\pi_i\left(E_{it}^K K_{it}\right)^{-\rho} + \left(1-\pi_i\right)\left(E_{it}^L L_{it}\right)^{-\rho}\right]^{-\frac{v}{\rho}}$$

where Y_{it} is the aggregate output, K_{it} and L_{it} are, respectively, the aggregate capital stock and labor, all in real terms and for region *i*, and E_{it}^j represents the level of efficiency of each input $j=K,L$. Following Arrow *et al*. (1961), $\pi_i \in (0,1)$ is the *distribution* parameter, reflecting capital intensity in production. Additionally, C is an efficiency parameter and ρ is the substitution parameter, with $\sigma = \frac{1}{1+\rho}$ being the elasticity of substitution between capital and labor whose value is very important for growth.[3] Note that, unlike Villacorta (2017) but the same as Kilponen and Viren (2010), who focused on a multi-country setting, we

3 See Azariadis (1993) and Barro and Sala-i-Martin (1993).

are assuming the same elasticity for all regions. Moreover, unlike Klump *et al.* (2000), I do not impose constant returns to scale in production, with $\nu > 0$.

Although expression (1) can be estimated directly using nonlinear methods, it has been standard practice to estimate the log-linearized version (Kmenta 1967). This procedure consists of taking logs of expression (1) and applying a second order Taylor expansion around $\rho = 0$, so that a simple least squares estimation can be performed[4]:

$$(2) \quad log(Y_{it}) = logC - \frac{\nu}{\rho} log\left(\pi_i \left(E_{it}^K K_{it}\right)^{-\rho} + (1-\pi_i)\left(E_{it}^L L_{it}\right)^{-\rho}\right) = logC + \nu\pi_i log\left(E_{it}^K K_{it}\right) + \nu(1-\pi_i) log\left(E_{it}^L L_{it}\right) - \frac{1}{2}\rho\nu\pi_i(1-\pi_i)\left[log\left(E_{it}^K K_{it}\right) - log\left(E_{it}^L L_{it}\right)\right]^2$$

This approach has been widely applied, though it suffers from an approximation bias that Thursby and Lovell (1978) showed was relevant for small samples, especially in estimating the elasticity of substitution and the more different it is from one.[5] Additionally, Diamond *et al.* (1978) proved that it is not feasible to jointly identify the technical progress parameters and the elasticity of substitution regardless of whether the function is log-linearized. In order to prevent this problem, standard practice since then has been to assume Hicks-neutrality, even after Antràs (2004) found that it could bias the results in favor of the Cobb-Douglas function.

As Klump *et al.* (2007) pointed out, the elasticity of substitution is always defined as a point elasticity, which means that it is related to one specific baseline point on one particular isoquant. Thus, the estimated parameters for the CES function lack theoretical or empirical meaning, given that they are dependent on the values of this point and the elasticity of substitution. Specifically, if we denote them by subscript 0:

$$\pi_{i0} = \frac{r_{i0} K_{i0}^{1/\sigma}}{r_{i0} K_{i0}^{1/\sigma} + w_{i0} L_{i0}^{1/\sigma}}$$

Klump *et al.* (2007) propose normalizing the CES function and representing it in consistent indexed numbers, since, in this case, the parameters have a clear empirical meaning.[6] Given that the baseline point holds at a particular moment in time $t = t_0$, following Klump *et al.* (2012), we assume the following functional form for the growth rates of efficiency of both inputs:

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4 Note that the last term in expression (2) disappears when $\rho = 0$.

5 This debate has a lot in common with the recent debate around the estimation of log-linearized consumption Euler equations (see Carroll, 2001).

6 Note that expression (1) is implicitly normalized at the point where inputs are equal to one.

(3) $$E_{it}^{j}=E_{i0}^{j}e^{\gamma_j(t-t_0)}$$

where γ_j, $j = K, L$, are the growth rates of capital and labor-augmenting technical progress and E_{i0}^{j} are the efficiency levels of each region at the baseline time t_0.

After normalizing, all members of the same family of production functions should share the same fixed point, but with different σ. To ensure this, we consider the following normalized values:

(4) $$E_{i0}^{L}=\frac{Y_{i0}}{L_{i0}}\left(\frac{1}{1-\pi_{i0}}\right)^{\frac{v}{\rho}};\ E_{i0}^{K}=\frac{Y_{i0}}{K_{i0}}\left(\frac{1}{\pi_{i0}}\right)^{\frac{v}{\rho}};\ e^{\gamma_K(t_0-t_0)}=e^{\gamma_L(t_0-t_0)}=1$$

Only at the baseline point, the distribution parameters π_{i0} and $1-\pi_{i0}$ are equal to the factor shares of income. Thus, the normalized CES production function will be:

(5) $$Y_{it}=Y_{i0}^{v}\left[\pi_{i0}\left(e^{\gamma_K(t-t_0)}\frac{K_{it}}{K_{i0}}\right)^{-\rho}+\left(1-\pi_{i0}\right)\left(e^{\gamma_L(t-t_0)}\frac{L_{it}}{L_{i0}}\right)^{-\rho}\right]^{-\frac{v}{\rho}}$$

Special cases, with Hicks-neutral technical progress, are Bentolila and Saint Paul (2003), where $N_0 = K_0 = Y_0 = 1$, or Antràs (2004), where $N_0 = K_0 = 1$.[7]

Assuming competitive markets and profit maximization, León-Ledesma *et al.* (2010) and Klump *et al.* (2012) show the effect of technical bias and capital deepening on factor income shares, what depends on the value of the elasticity of substitution.

The proposal by Klump *et al.* (2007) consists of estimating the normalized CES production function within a supply-side system of equations including the first-order conditions of profit maximization (FOC). So, this system comprises equation (5) and the two FOC[8]:

(5) $$Y_{it}=Y_{i0}^{v}\left[\pi_{i0}\left(e^{\gamma_K(t-t_0)}\frac{K_{it}}{K_{i0}}\right)^{-\rho}+\left(1-\pi_{i0}\right)\left(e^{\gamma_L(t-t_0)}\frac{L_{it}}{L_{i0}}\right)^{-\rho}\right]^{-\frac{v}{\rho}}$$

7 As is well-known, Hicks neutrality requires $\gamma = \gamma_K = \gamma_L > 0$, while Solow neutrality requires $\gamma_K > 0$, $\gamma_L = 0$, and Harrod neutrality $\gamma_K = 0$, $\gamma_L > 0$, while $\gamma = > 0 \neq \gamma_L > 0$ indicates general factor-augmenting technical progress.

8 The analysis by Klump *et al.* (2007) differs from ours in that they log-linearize the function and consider a mark-up.

(6)
$$\pi_{it} = \pi_{i0}\left(\frac{Y_{it}/Y_{i0}}{K_{it}/K_{i0}}\frac{1}{e^{\gamma_K(t-t_0)}}\right)^{\frac{\rho}{v}}$$

(7)
$$1-\pi_{it} = \left(1-\pi_{i0}\right)\left(\frac{Y_{it}/Y_{i0}}{L_{it}/L_{i0}}\frac{1}{e^{\gamma_L(t-t_0)}}\right)^{\frac{\rho}{v}}$$

León-Ledesma *et al*. (2010) review the available methods to estimate the CES function through Monte-Carlo analysis, concluding in favor of the system of equations. However, Luoma and Luoto (2011) have criticized the use of Feasible Generalized Nonlinear Least Squares (FGNLS) to estimate the system of equations, given that it is not consistent when the errors of the equations are correlated; they instead propose a Bayesian full information method.

Although Sturgill (2012) shows that the estimation of production functions with only capital and labor can be problematic,[9] difficulties with Spanish regional data prevent us from using more than two factors of production in our empirical work. In any case, we follow Duffy and Papageorgiou (2000) in considering labor data, both raw and adjusted for human capital, given their relevance for economic growth (Romer 1986). Like Tallman and Wang (1994), we define the human capital stock as follows:

$$H_{it} = E_{it}^{\varnothing}$$

where E_t is the average years of schooling of the labor force, and $\varnothing > 0$ a parameter capturing the returns to education. So, we define labor adjusted by human capital (HL_{it}) as

(8)
$$HL_{it} = H_{it} x L_{it} = E_{it}^{\varnothing} L_{it}$$

Given that the estimation of $\varnothing$ has proven to be very problematic, especially with nonlinear regression, we follow Lucas (1988), Rebelo (1991) and Duffy and Papageorgiou (2000) in setting $\varnothing$ equal to one. We will use both L_{it} and HL_{it} in estimating the CES production function[10].

Evidently, normalization requires the researcher to choose the *appropriate* values for the baseline point. Klump *et al*. (2007) suggest using available data and calculating them through sample averages. However, except with the log

9 In this respect, Sturgill (2012) found that non-reproducible factors of production shares decrease with the stage of economic development in contrast to those of reproducible factors.

10 We consider that raw labor data and labor data adjusted by human capital enter the CES function in the same way. Also Gumbau and Maudos (2006) consider the effect of human capital on the production function.

linear CES function, there is no reason why the sample should exactly coincide with the implicit fixed point of the empirical function. Therefore, following these authors, we introduce an additional parameter ζ, so that $Y_{i0} = \zeta \bar{Y}_i$, $K_{i0} = \bar{K}_i$, $L_{i0} = \bar{L}_i$, $\pi_{i0} = \bar{\pi}_i$, $t_0 = \bar{t}$, where the bar refers to sample averages.[11] Klump *et al*. (2007) use geometric averages to determine the baseline point values for the output and inputs, and arithmetic averages for those of capital income share and time.

The literature on normalized CES functions has paid special attention to the distribution parameter, π_{it}, although unlike with the Cobb-Douglas function, it does not have to be equal to the capital income share; in fact, it is only required that $\pi_{it} \in [0,1]$. As Klump *et al*. (2007) point out, it can be directly calculated from data when fixing the baseline point values, or, alternatively, it can be estimated jointly with other parameters. They suggest using their estimate as a criterion for judging how reasonable the results are. At any rate, there is no universally agreed approach: while Klump *et al*. (2007) estimate it, León-Ledesma *et al*. (2010 and 2015) do not.[12]

3. The Data and the Point of Normalization

In this paper, I perform a nonlinear estimation of the CES production function using different methods. First, it is estimated the non-normalized CES function, in levels and in logs, following the Kmenta approach. Next, it is estimated their normalized version, comparing their results with those previously obtained for the non-normalized one. Finally, I compare all these results with those obtained by estimating the system of equations (5) to (7) using both nonlinear feasible least squares (FGNLS or NLSUR) and the nonlinear generalized method of moments (NLGMM), robust to correlated errors.

Our regional data merge two Spanish statistical sources. I have taken the GDP in constant 2010 euros, the employment and workforce data from RegData, the Fundación de Estudios de Economía Aplicada (FEDEA) database, and the productive capital stock in constant 2010 euros from the Instituto Valenciano de Investigaciones Económicas (IVIE) database.[13] Although RegData covers the period from 1955 to 2016, IVIE's capital series are only available from 1964 to 2013. All other variables used, such as labor income share, have been taken from the RegData database.[14]

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11 ζ deviates from one when sample averages are different from the respective baseline point values.

12 Klump *et al.* (2007) obtained an estimate for the US economy slightly above 0.2, while León-Ledesma *et al.* (2010) fixed it at 0.4. León-Ledesma *et al.* (2015) point out that setting a different value does not affect the results.

13 The RegData database can be downloaded from http://encifras.fedea.net/, and the capital data from https://www.ivie.es/es_ES/bases-de-datos/capitalizacion-y-crecimiento/el-stock-y-los-servicios-de-capital/.

14 I have excluded from the analysis the autonomous cities of Ceuta and Melilla.

There is no consensus in the literature on the most suitable measure of labor for estimating production functions: both the workforce and the aggregated worked hours are used. In line with Duffy and Papageorgiou (2000), and as Gumbau and Maudos (2006), I use the workforce. I have also used the value added of production to measure output, though we have confirmed that using GDP does not change the results.

As Krueger (1999) and Gollin (2002) point out, it is difficult to disentangle labor income from capital income in available self-employed income data. Nevertheless, the RegData database provides an estimate of aggregate labor income including labor income of self-employed workers. I note that it provides a very reasonable average total labor income share of 0.66 (0.59 in 2015) for the period 1955-2015.

In this paper, I follow Klump *et al.* (2007) in normalizing the CES production function, taking both the arithmetic and geometric averages of variables as baseline point values. Basically, these values could be determined by any reasonable criterion. In fact, Mallick (2012) and Villacorta (2017) use the initial values of the sample, and Kilponen and Viren (2010) use both, sample country averages and panel averages as baseline values. Nevertheless, given that some variables increase substantially over our long sample period, I have taken 1974 onwards as the reference period to calculate the averages.[15] Although the data has a panel structure, the normalization circumvents the need to demean or difference the series to eliminate regional fixed effects, a very complex task with the nonlinear CES function.[16]

The available empirical evidence for Spain has not produced a consensus on the value of the elasticity of substitution. Many of the first attempts at estimation have been within multi-country studies: the estimates obtained by Duffy and Papageorgiou (2000) and by Villacorta (2017) were above one, whereas Mallick (2012) estimated a value below one. Raurich *et al.* (2012), following Antràs (2004), obtained an estimate above one with time series data, while Doraszelski and Jaumandreu (2018) reported estimates of around 0.5 using industrial data.

4. Empirical Results

In Table 1 are presented the results of the nonlinear estimation of the CES production function, in levels and in logs, assuming Hicks-neutral technical progress. Cols. (1) to (4) present the results of estimating the non-normalized function, while cols. (5) to (10) present those of estimating the normalized one. At the bottom of every Table the results of the ADF test of the residuals are shown. I also estimate the model both with and without constant returns to scale, i.e., imposing $\nu = 1$ or estimating it. As can be seen, the results show a very good econometric fit, measured by the $\bar{R}^2$, while the estimated elasticity

15 I have checked that the results are robust to this decision.

16 To the best of my knowledge, only Duffy and Papageorgiou (2000) have attempted this task, with mixed results.

of substitution is always well below one. This result does not change with the returns to scale assumption, given that ν is estimated very close to one. For the non-normalized function (cols. (1) to (4)), the estimate for π is very low, 0.2 at most. The estimated rate of technical progress, λ, is extremely low, especially for the model in levels, for which it is not statistically significant.[17] Given that this model provides a similar estimate for the elasticity of substitution and a more reliable one for the distribution parameter, while at the same time avoiding the approximation bias, I use it to estimate the CES function for the rest of the paper.

TABLE 1
NONLINEAR SINGLE EQUATION ESTIMATES

					Normalized					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(ν = 1)		(ν = 1)		(ν = 1)		(ν = 1)		(ν = 1)	
	Lev.	Lev.	Log.	Log.	Lev.	Lev.	Lev.	Lev.	Lev.	Lev.
C	0.451	0.370	0.293	0.279						
	0.131	0.098	0.063	0.065						
ζ					1.024	1.156	1.024	1.155	1.011	1.127
					0.018	0.057	0.019	0.056	0.005	0.055
π	0.101	0.204	0.032	0.045	0.428	0.432	0.424	0.427		
	0.148	0.147	0.069	0.084	0.143	0.126	0.157	0.139		
ρ	2.895	2.092	3.408	3.135	2.814	2.911	3.168	3.273	3.083	3.198
	0.946	0.291	1.686	1.472	0.447	0.376	0.465	0.416	0.246	0.269
λ	0.002	–0.001	0.009	0.008	–0.001	0.001			0.001	0.001
	0.005	0.003	0.003	0.004	0.002	0.002			0.001	0.001
$\lambda_{64\text{-}73}$							–0.002	–0.001		
							0.003	0.003		
$\lambda_{74\text{-}13}$							–0.001	0.001		
							0.002	0.002		
ν		1.085		1.025		0.972		0.972		0.975
		0.023		0.034		0.011		0.011		0.010
σ	0.257	0.323	0.227	0.242	0.262	0.256	0.240	0.234	0.245	0.238
N obs.	850	850	850	850	850	850	850	850	850	850
$\bar{R}^2$	0.980	0.982	0.972	0.973	0.997	0.997	0.997	0.997	0.997	0.997
ADF	0.001	0.000	0.000	0.000	0.008	0.004	0.001	0.001	0.009	0.006

Note: The Tables report the estimated parameters and, below, the standard errors. We also report the p-value of the ADF test for the residuals.

17 The estimate obtained by Duffy and Papageorgiou (2000) for the log-linearized no normalized CES was always negative and statistically significant, what they attributed to the 70s' productivity slowdown.

In Table 1 I also compare the results of the estimation of the normalized CES function in levels when π is left free (cols. (5) to (8)) or is taken from the data (cols. (9) and (10)). As can be seen, the results are very similar in both cases. On the one hand, the parameter ζ, measuring the adjustment of normalization, is close to one, but worsens when ν is left free; on the other, the results improve when π is taken directly from the data.[18] The elasticity of substitution is now estimated at slightly above 0.2, very near to the estimate with the non-normalized equation. I note that these values are very close to the estimate of 0.127 reported by Mallick (2012) using Spanish time series. Given that the estimate for λ is not statistically significant, I follow Duffy and Papageorgiou (2000) in estimating the model with two different rates of technical progress, before and after 1973 (cols. (7) and (8)), in an attempt to identify a hypothetical structural change. As can be seen, the estimates are similar both in value and in statistical significance, and also similar to the estimate for the entire period. The only noteworthy difference is a very small reduction in the estimated elasticity of substitution. Additionally, the estimate of π is very reasonable, around 0.4, and the results do not change when I set it at their sample value (cols. (5) and (6) vs. cols. (9) and (10)), except for a slight improvement in the adjustment parameter. I thus substitute it for their sample average from here on.

Table 2 presents the results of estimating the system of equations (5) to (7), both by FGNLS or NLSUR (cols. (1), (2), (5) and (6)) and by NLGMM (cols. (3), (4), (7) and (8)). In Cols. (5) to (8) labor is adjusted by human capital.[19] As in Table 1, I compare the results when I impose $\nu=1$ or I leave it free. They show a very reasonable goodness of fit, measured by the $\overline{R}^2$ for the FGNLS and by the Hansen test for the NLGMM, and the estimate for the elasticity of substitution remains below one. Interestingly, the FGNLS estimates obtained with raw labor data are bigger than the NLGMM ones, but the opposite is true for those obtained with labor adjusted by human capital. Considered as a whole, the results in Tables 1 and 2 support the constant returns to scale hypothesis: when it is estimated, ν is very close to one, and when imposed, the results do not change significantly. The estimates for the adjustment parameter ζ indicate a worst fit with labor adjusted by human capital. Finally, the estimate for the rate of Hicks-neutral technical change increases with the normalized CES function with the system of equations, especially within the NLGMM estimates, although, similarly to Duffy and Papageorgiou (2000), it is negative.[20]

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18 Our estimates for ζ are bigger than those obtained by Klump *et al.* (2007), ranging from 1.00 to 1.04. However, it should be borne in mind that we estimate the model in levels, while they do it in logs.

19 On the effect of human capital in Spanish productivity, see Serrano (1997) and Carrion-i-Silvestre and Surdeanu (2016).

20 As I have already mentioned, changing the period for the baseline values in normalization does not affect the results. In this respect, I have check it with different periods used for computing the baseline values; additionally, I have verified that changing $\emptyset$ or considering, as Bils and Klenow (2000), $HL_{it} = e^{\emptyset(E_{it})} L_{it}$, where $\emptyset\,(E_{it})$ is the return to education and E_{it} are the years of schooling, does not affect the results either. In this case, following

TABLE 2
NORMALIZED NONLINEAR SYSTEM ESTIMATES

	L_{it}				HL_{it}			
	FGNLS	FGNLS	NLGMM	NLGMM	FGNLS	FGNLS	NLGMM	NLGMM
	($\nu = 1$)		($\nu = 1$)		($\nu = 1$)		($\nu = 1$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ζ	0.995	1.033	1.095	1.100	1.081	1.173	1.146	1.138
	0.008	0.015	0.008	0.010	0.007	0.018	0.016	0.013
ρ	1.872	1.674	3.802	2.553	4.507	3.924	2.656	2.781
	0.227	0.248	0.582	0.225	0.629	0.745	0.210	0.218
λ	0.001	0.001	–0.006	–0.010	–0.009	–0.008	–0.018	–0.017
	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001
ν		0.990		1.001		0.980		1.001
		0.002		0.001		0.003		0.001
σ	0.348	0.374	0.208	0.281	0.182	0.203	0.274	0.264
N obs.	850	850	850	850	850	850	850	850
$\bar{R}^2$	0.997	0.997			0.996	0.996		
Hansen			4.944	5.810			8.959	7.266
			0.976	0.971			0.941	0.967
ADF_Y	0.000	0.040	0.012	0.019	0.000	0.000	0.000	0.000
$ADF_{\pi K}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$ADF_{\pi L}$	0.000	0.000	0.043	0.000	0.000	0.001	0.000	0.004

Note: The instruments in col. (3) are:
- eq. 1: the 2nd and 3rd differences of the log of GDP and a constant.
- eq. 2: the 2nd and 3rd differences of occupied (O), real added value of output (VA), labor force (LF) and a constant.
- eq. 3: the 2nd and 4th differences of VA, the 3rd and 4th differences of LF and the 4th difference of O and a constant.

The instruments in col. (4) are the same as in col. (3), adding for eq. 1 the 2nd and 3rd differences of O.

The instruments in cols. (7) and (8) are:
- eq. 1: the 2nd to 4th differences of the log of GDP, the 2nd and 4th differences of O, the 2nd difference of the capital income share (KS) and a constant.
- eq. 2: the 2nd and 3rd differences of O, VA, LF and a constant.
- eq. 3: the 2nd and 4th differences of VA, the 3rd and 4th differences of LF, the 2nd difference of O and a constant.

In Table 3 I abandon the Hicks-neutrality assumption, allowing for different rates of factor-augmenting technical progress. It is noteworthy that the estimate of the elasticity of substitution more than doubles with respect to Table 2. In addition, the estimates for both λ are now meaningful, compared to previous results. Notably, I obtain a positive growth rate of capital-augmenting technical progress, averaging above 2% and reaching more than 6% in one case. At the

Requena (2015), I have tried values of the rate of return to education ranging from 8% to 10%. All these results are available upon request.

TABLE 3
NORMALIZED NONLINEAR SYSTEM ESTIMATES

	L_{it}				HL_{it}			
	FGNLS	FGNLS	NLGMM	NLGMM	FGNLS	FGNLS	NLGMM	NLGMM
	(ν = 1)		(ν = 1)		(ν = 1)		(ν = 1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ζ	0.990	1.030	0.957	0.969	1.079	1.111	1.071	1.105
	0.006	0.032	0.010	0.009	0.006	0.025	0.009	0.028
ρ	0.612	0.544	0.223	0.173	1.027	0.818	0.432	0.402
	0.137	0.233	0.107	0.070	0.200	0.272	0.240	0.253
λ_K	0.027	0.031	0.048	0.056	0.016	0.020	0.052	0.061
	0.005	0.011	0.019	0.019	0.003	0.007	0.021	0.026
$\lambda_{L/HL}$	–0.008	–0.009	–0.016	–0.019	–0.017	–0.019	–0.029	–0.033
	0.002	0.005	0.008	0.008	0.001	0.003	0.008	0.011
ν		0.990		0.995		0.992		0.996
		0.006		0.004		0.004		0.006
σ	0.620	0.648	0.818	0.853	0.493	0.550	0.698	0.713
N obs.	850	850	850	850	850	850	850	850
$\bar{R}^2$	0.997	0.997			0.997	0.997		
Hansen			15.389	15.350			9.868	17.654
			0.880	0.846			0.873	0.610
ADF_Y	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000
$ADF_{\pi K}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$ADF_{\pi L}$	0.000	0.000	0.040	0.016	0.000	0.000	0.006	0.001

Note: The instruments in cols. (3) and (4) are:
- eq. 1: the 2nd to 4th lag of the log of O, the 2nd lag of VA and a constant.
- eq. 2: the 2nd to 4th differences of VA, O and KS, the 3rd and 4th differences of LF and a constant.
- eq. 3: the 2nd to 4th differences of VA, LF, KS and a constant.

The instruments in col. (7) are:
- eq. 1: 2nd to 4th lags of the log of VA, the 2nd to 5th differences of the GDP divided by LF, and the 2nd, 3rd and 5th differences of labor force adjusted by human capital (LFH).
- eq. 2: the 2nd to 4th differences of the labor income share (LS) and the 2nd lag of occupied adjusted by human capital (OH).
- eq. 3: the 2nd to 4th differences of KS, and the 2nd, 4th and 5th differences of the log of OH.

The instruments in col. (8) are:
- eq. 1: the 2nd to 4th lags of the log of VA, the 2nd to 5th differences of the GDP divided by LF, and the 2nd to 4th differences of the log of O and a constant.
- eq. 2: the 2nd to 4th differences of LS, the 2nd to 4th lags of the log of O, the 2nd to 4th differences of the KS and a constant.
- eq. 3: the 2nd to 4th differences of the KS, and the 3rd and 4th differences of the GDP divided by O.

same time, I obtain a negative growth rate of labor-augmenting technical progress, averaging below –2%, with very similar results with raw labor data and adjusted by human capital. Finally, the adjustment parameter ζ shows similar behavior to previous Tables, increasing with labor adjusted by human capital data, and the estimate for ν is again very close to one.

For the US economy, Klump *et al*. (2007) obtained factor-augmenting technical progress rates of 0.004 and 0.015 for capital and labor, respectively, with an elasticity of substitution between 0.5 and 1. This evidence has raised some controversy. Assuming an elasticity below one, Lawrence (2015) combines labor-augmenting technical progress with the fall in the relative price of capital to explain the decline in the US labor income share, although he argues that there is a discrepancy between the increase observed in the *measured* capital-labor ratio and the fall observed in the *effective* ratio. Alternatively, Karabarbounis and Neiman (2014) consider an elasticity above one, explaining the decline in the US labor income share by the fall in the price of investment, although they assume that the rate of capital-augmenting technical progress is orthogonal to shocks.

Thus, the results indicate that the behavior of technical progress in the US differs from that in Spain. They are in line with those obtained in the multi-country panel study by Villacorta (2017), although they contradict those obtained by Doraszelski and Jaumandreu (2018) with industrial data.[21] Complicating matters, while the former study obtained an elasticity of substitution above one, the second reported a value below one. In any case, it seems very unlikely that the same reasons could explain the recent decline in the labor income share in both Spain and in the US, given the extremely different behavior of their respective labor markets. In this respect, the fall in the Spanish labor share has been more pronounced since 1975, being smaller today, as the Spanish capital-labor ratio has experienced a catch-up process with the US ratio.[22] Given the high degree of hysteresis of the Spanish unemployment rate, reaching values above 25% twice in the last 30 years,[23] Spanish labor productivity should be very high in relative terms, whereas we observe exactly the opposite, along with a relatively low total factor productivity.[24] Thus, our results can be taken as evidence supporting labor-saving innovations (Boldrin and Levine 2002; Zuleta 2008) or labor-eliminating

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21 Villacorta (2017) obtains –1.1% and 1.7%, respectively, for the Spanish rates of labor- and capital-augmenting technical progress.

22 The correlation coefficient between the national aggregates of both variables with my data amounts to –0.8091, with a *p-value* of 0.0000. After detrending a linear trend, the coefficient falls to –0.0753, with a *p-value* of 0.6034, rejecting the existence of a statistically significant relationship between them. So, imposing Hicks' neutrality provides the same result as estimating the model without a trend, what explains the highest estimated elasticity when it is not imposed. I am grateful to an anonymous referee for suggesting both the calculation of these correlations and its connection to the results.

23 In fact, from 1975 to 2019, the Spanish unemployment rate shows a growing linear trend, in contrast to US unemployment rate.

24 On labor productivity in Spain and the Spanish labor market, see Hospido and Moreno-Galbis (2015) and Bande *et al.* (2019). Spain not only presents a low labor productivity in relative terms; it is also the only economy in the EMU that exhibits a counter-cyclical pattern of this variable. Jalón *et al.* (2017) shows that Spanish labor productivity shifted from a strongly procyclicality to a countercyclical pattern since 1984, coinciding with the legislative reform that introduced the temporary contracts.

technical progress (Seater, 2005; Peretto and Seater, 2013), simultaneously leading to capital deepening and the fall in the labor income share.[25, 26]

Tables 1, 2, and 3 confirm the conclusion drawn by León-Ledesma *et al.* (2010) regarding the clear advantages of normalization for estimating the CES function, especially to jointly identify the elasticity of substitution and the parameters of technical progress. They do not support labor-augmenting technical progress for Spain and, at the same time, place the Spanish elasticity of substitution clearly below one. The discrepancies with the results reported by Doraszelski and Jaumandreu (2018) could be due to the fact that those authors used data from the industrial sector only rather than the overall economy, and because they use a different measure for labor.[27]

There has been growing interest recently in the relationship between the elasticity of substitution, the efficiency of the capital accumulation process and economic growth.[28] In this regard, Duffy and Papageorgiou (2000) extract different subsamples of countries depending on the initial value of capital per worker, attempting to identify differences in the elasticity depending on the level of economic development. In addition, Mallick (2012) regresses the rate of economic growth on elasticities previously estimated, finding a strong and robust relationship.[29] In this context, I have extracted two subsamples depending on whether, in the first year of the sample, the regions are above or below the average for real capital per worker; I then use these subsamples

[25] Acemoglu (2007) shows how an equilibrium technology can exist that be relatively biased toward the more abundant productive factor, in the sense that a change in technology, induced by small changes in factor supplies, increases their demand or their marginal product. Additionally, Acemoglu and Restrepo (2018, 2019) and Ray and Mookherjee (2020) analyze technologies rendering labor redundant.

[26] Recently, Seater and Yenokyan (2019) develop a model with, simultaneously, factor-augmentation and factor-elimination, and they prove that factor-augmenting technical change is a misspecification when the second is present. This could explain the obtaining of a negative estimate of the rate of labor-augmenting technical change in the Spanish economy.

[27] Young (2013) estimated a normalized CES production function within a system of equations for 35 US industries, finding an aggregate elasticity of substitution less than unity and also finding that technical change "appears to be net labor-augmenting" (p. 861); specifically, he obtained net labor-augmentation for a different number of industries depending on the estimation method used, 12, 18 or 29 out of 35.

[28] The relationship between the elasticity of substitution and economic growth has always featured in normalization analysis; see, for example, De La Grandville (1989) and Klump and De la Grandville (2000).

[29] Nevertheless, Kilponen and Viren (2010) find that the correlation between the elasticity of substitution and growth rates is virtually zero; additionally, the conclude that the "evidence on a varying elasticity of substitution is rather weak" (page 313).

to estimate the elasticity of substitution.[30, 31] In this exercise, we assume constant returns to scale. In Table 4 we present the results obtained by estimating the normalized system and using raw labor data. As can be seen, the Hicks-neutral technical change assumption provides very similar results for the two subsamples and the entire sample. The estimated elasticities of substitution for both are similar, around 0.2/0.3, and the adjustment parameter ζ is also similar. Finally, as in Tables 2 and 3, the estimated elasticity of substitution increases significantly when I allow for different rates of technical progress, especially for the high capital per worker sample. In any case, the estimated elasticities are still significantly different from one. These results seem to indicate that the model's technological assumptions condition the estimation of the elasticity of substitution. Additionally, this relationship also seems to be affected by the specific value of the capital-labor ratio, although deeper research would be needed. In this respect, Young (2013) found that the estimated elasticity varies between industrial sectors which differ in their technological and productive characteristics.

When the Hicks-neutrality assumption is abandoned, the adjustment parameter ζ decreases slightly for both subsamples. Notably, the markedly different estimated rates of technical progress for the two factors in both samples also indicates very different regional technical progress processes. The high capital per worker sample provides an estimate for the rate of capital-augmenting technical progress of around 10%, while the estimated rates for labor-augmenting technical progress are negative, at around –4/4.5%. The results for the other sample are not conclusive, given that both estimators provide different results. This could well be explained by the smaller sample size. In any case, they constitute evidence of an important degree of regional heterogeneity in Spain, both within and between the samples.[32]

In Table 5 I replicate this exercise using labor adjusted by human capital. As with the total sample, the estimated ζ increases slightly, although, not surprisingly, the estimates are less precise. The estimated elasticities are lower than those obtained using raw labor data, but the rest of the results are very similar. Again, we cannot conclusively identify a clear pattern for both samples, and the Hicks-neutrality assumption is a key determinant of the estimated value for

[30] I choose not to use initial income per worker as benchmark in order to avoid selection bias. Moreover, rather than using the average, Duffy and Papageorgiou (2000) divide their sample into four groups of equal size. Our smaller sample has prevented from extracting more than two groups.

[31] The regions below the average in 1965 were Andalusia, the Balearic Islands, Castilla-La Mancha, the Valencian Community, Extremadura, Galicia, Murcia, La Rioja and the Canary Islands. Above-average regions were Aragón, Asturias, Cantabria, Castilla-León, Catalonia, Madrid, Navarre and the Basque Country.

[32] Bande *et al*. (2019) find that labor productivity has followed a similar path in low- and high-income Spanish regions, although with a very different pattern of employment behavior in both.

TABLE 4
NORMALIZED NONLINEAR SYSTEM ESTIMATES

	L_{it}							
	High Capital per Worker Sample				Low Capital per Worker Sample			
	FGNLS	FGNLS	NLGMM	NLGMM	FGNLS	FGNLS	NLGMM	NLGMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ζ	0.993	0.983	1.091	0.955	0.991	0.959	1.112	0.984
	0.010	0.006	0.015	0.010	0.008	0.011	0.009	0.003
ρ	1.767	0.055	5.789	0.069	2.134	0.473	2.815	0.100
	0.258	0.009	0.660	0.026	0.290	0.095	0.751	0.030
λ	0.001		–0.004		0.002		–0.009	
	0.001		0.001		0.001		0.002	
λ_K		0.122		0.087		–0.052		0.075
		0.008		0.032		0.006		0.019
$\lambda_{L/HL}$		–0.054		–0.035		0.051		–0.036
		0.004		0.014		0.005		0.010
σ	0.361	0.948	0.147	0.935	0.319	0.679	0.262	0.909
N obs.	400	400	400	400	450	450	450	450
$\overline{R}^2$	0.998	0.998			0.996	0.997		
Hansen			2.393	4.626			2.258	3.917
			0.999	0.913			0.999	0.998
ADF_Y	0.032	0.000	0.023	0.000	0.002	0.000	0.001	0.001
$ADF_{\pi K}$	0.004	0.000	0.001	0.000	0.000	0.000	0.000	0.008
$ADF_{\pi L}$	0.000	0.000	0.020	0.000	0.000	0.008	0.001	0.000

Note: The instruments in cols. (3) and (7) are:
- eq. 1: the 2nd and 3rd differences of the log of real GDP and a constant.
- eq. 2: the 2nd and 3rd differences of the VA, O, LF and a constant.
- eq. 3: the 2nd and 4th differences of the VA, the 4th difference of O, the 3rd and 4th differences of LF and a constant.

The instruments in col. (4) are:
- eq. 1: the 2nd and 4th lags of the log of O, the 2nd difference of the log of VA and a constant.
- eq. 2: the 2nd difference of O, VA, the 3rd difference of LF and the 3rd and 4th differences of the log of VA.
- eq. 3: the 2nd and 4th differences of VA, the 3rd difference of LF and a constant.

The instruments in col. (8) are:
- eq. 1: the 2nd and 4th lags of VA, the 2nd and 3rd differences of K and a constant.
- eq. 2: the 2nd and 4th differences of the VA, the 3rd and 4th differences of LF, of LFH and of KS.
- eq. 3: the 2nd and 4th differences of VA, the 3rd difference of LF, K and a constant.

the elasticity. Both samples yield a similar FGNLS estimate for it, of around 0.2, and a negative and statistically significant rate of Hicks-neutral technical progress, of around –0.01. However, unlike in Table 4, the two estimates for both rates of technical progress with the low capital per worker sample are very similar, while the opposite is true for the complementary sample. In my opinion, this confirms a high degree of regional heterogeneity in the sample.

TABLE 5

NORMALIZED NONLINEAR SYSTEM ESTIMATES

	HL_{it}							
	High Capital per Worker Sample				Low Capital per Worker Sample			
	FGNLS	FGNLS	NLGMM	NLGMM	FGNLS	FGNLS	NLGMM	NLGMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ζ	1.086 0.008	1.070 0.007	1.146 0.029	1.083 0.007	1.072 0.008	1.050 0.013	1.133 0.014	1.018 0.027
ρ	5.287 0.657	0.062 0.011	2.626 0.283	0.735 0.310	4.101 0.799	0.410 0.096	3.185 0.762	0.895 0.110
λ	–0.009 0.001		–0.019 0.003		–0.008 0.001		–0.015 0.002	
λ_K		0.111 0.008		0.038 0.014		–0.058 0.007		–0.052 0.003
$\lambda_{L/HL}$		–0.063 0.004		–0.022 0.004		0.035 0.004		0.092 0.008
σ	0.159	0.942	0.276	0.576	0.196	0.709	0.239	0.528
N obs.	400	400	400	400	450	400	450	450
$\bar{R}^2$	0.997	0.998			0.995	0.997		
Hansen			7.122 0.981	9.119 0.908			4.316 0.987	4.843 0.993
ADF_Y	0.001	0.000	0.008	0.014	0.005	0.000	0.003	0.004
$ADF_{\pi K}$	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.031
$ADF_{\pi L}$	0.000	0.000	0.002	0.008	0.000	0.011	0.008	0.000

Note: The instruments in col. (3) are:

- eq. 1: the 2nd to 4th differences of the log of real GDP, the 2nd and 4th differences of O, the 2nd and 4th difference of KS and a constant.
- eq. 2: the 2nd and 3rd differences of O, of the VA, LF and a constant.
- eq. 3: the 2nd and 4th differences of VA, the 3rd and 4th differences of LF and the 4th difference of O and a constant.

The instruments in col. (4) are the same as in col. (7) of Table 3.
The instruments in col. (7) are the same as in cols. (3) and (7) of Table 4.
The instruments in col. (8) are the same as in col. (8) of Table 4.

In any case, taken together, the results of Tables 4 and 5 do not support the hypothesis of a different elasticity of substitution at the regional level depending on the initial capital per worker.[33]

[33] Duffy and Papageorgiou (2000) are not conclusive about this hypothesis. Additionally, although Mallick (2012) finds a robust relationship between the growth rate and the

5. Conclusion

The decline in the labor income share in developed countries has called into question the use of the Cobb-Douglas production function in macroeconomic analysis. In parallel, the normalization technique and the improvement in nonlinear estimation procedures have encouraged the estimation of the CES function. In this context, we have combined information from the regional database RegDat with capital data from the IVIE database to estimate a CES production function for Spain. My main aim has been to estimate the elasticity of factor substitution, which I have done through different empirical strategies (levels vs. logs; normalized vs. non-normalized; single equation vs. system of equations), and then compared the results.

According to the results, the CES function shows a good econometric fit to the regional Spanish data. We have obtained an estimate below one for the Spanish elasticity of substitution. This can be considered a relevant finding, given the current controversy on its value and the evolution of the labor income share. In addition, the results support the hypothesis of constant returns to scale for the Spanish economy.

I have also verified that the Hicks-neutrality assumption generates a downward biased estimate of the elasticity of substitution and masks the true characteristics of Spanish technical progress. Thus, by allowing for different rates of factor-augmenting technical progress, we have obtained more reasonable results and an estimate for the elasticity doubled in value, albeit remaining below one. Nevertheless, I have also obtained a negative growth rate of labor-augmenting technical progress. Additionally, the results confirm the conclusion of León-Ledesma *et al.* (2010) on the superiority of the system of equations approach to estimate the CES function, with the added advantage that it circumvents the identification problem. The results also support the hypothesis on labor-saving technical progress for the Spanish case.

Finally, following Duffy and Papageorgiou (2000), I have decomposed our regional sample into smaller subsamples depending on the value of initial capital per worker. Using these subsamples, I have been able to detect differences in the econometric fit of the CES function and in the characteristics of technical progress at the regional level, but not in the elasticity of substitution, or at least not clear differences. As such, the results do not allow to conclude in favor of a clear relationship between the level of economic development and the elasticity of substitution.

Further research should seek to verify whether the use of a different measure for labor, such as total hours worked, could affect the results. This could be relevant for the Spanish case, given the behavior of unemployment in Spain.

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elasticity of substitution, he also finds evidence indicating that it is, at the very least, highly complex: a positive elasticity is estimated for the US, above that of most of the European countries, but below that of many less developed countries, such as Chad, Lesotho, Mauritius or Paraguay, among others.

At the same time, the unusual characteristics of the Spanish labor market make it especially interesting to check if a modified CES function incorporating a mark-up would provide different results. Finally, it could be relevant also to check if spillover effects between regions are important.

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