What is the Marginal Productivity of Apprentices ?

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In this article we evaluate the productivity of apprentices during their training within French and German firms. The econometric analysis is based on two cross-section datasets, one of whom was constructed by matching two INSEE firm-level surveys whereas the second one is an extraction of the IAB - firm panel. We estimate Cobb-Douglas and Translog production functions combined with a probit selection equation which allows to control for the situation where a given firm does not train apprentices. Concerning the productivity of apprentices we find a structural difference between small and large firms. We find that for small firms in France and Germany negative net costs during the training period may be a sufficient condition to train. Especially with small German firms we find a strong involvement of apprentices in the production process. For larger firms the current production argument does not seem to hold anymore in order to explain the observed behaviour.

1. Why estimate the marginal productivity of apprentices ?

Recently there has been substantial development in the theoretical literature concerning the motivation of firms to invest in human capital of a not purely firm-specific type and especially to invest in apprenticeship training.[3] The usual reasons for this type of behaviour may basically be divided into two arguments.[4] The first motivation may come from a reduction of costs of non-qualified work : Apprentices in this case are hire because they are cheaper than unskilled workers while accomplishing the same tasks. Additionally, by hiring apprentices firms may more easily and at a lower price adapt their unskilled workforce to business cycle needs. This motivation is called the *current production argument.*

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[3] See for a review of this literature the paper of Acemoglu and Pischke (1999).

[4] See for an early classification Lindley (1975).

A second argument proposes that firms may want to invest in human qualified capital, especially if they face shortages on the labour market for skilled work. In this case their motivation will depend on the expected composition of the qualifications offered in the open labour market as well as their minimum requirement of individual ability as well as their level firm-specific human capital employed in the production process. We shall call this the *investment argument.*

Whereas the investment argument is related to an expected profit, the current production argument is based on the comparison of the production value of apprentices during their training period with the direct costs of training. Recent results (see Schwerdt and Bender, 2000) show that in France the current production argument seems to be more relevant because of relatively costly unskilled labour.[5] The same may be true for Germany where the results of Bardeleben et al. (1995) showed that for small and medium sized firms the current production argument may be a sufficient condition to train apprentices. However, for the time being there is no reliable evaluation of the actual productivity of apprentices during their training that may give a mean test the relevance of this argument. This is what we try to do in this paper . For this purpose we use two datasets. The first contains about 10000 French firms in observed in 1992 which come from the *Enquête sur le Coût de la Main d'Oeuvre et sur la Structure des Salaires* (ECMOSS) which is matched to the *Enquête sur les Bénéfices Industriels et Commerciaux* (BIC), both surveys of the INSEE. The second dataset is an extraction of the German firm panel of the IAB (*Institut für Arbeitsmarkt- und Betriebsforschung*). It allows us to observe 4500 firms of all industrial sectors.

The estimations done in this paper are based on Cobb-Douglas and Translog production functions. As we only observe apprentices in a subgroup of the firms in our datatsets we model a probit selection equation resulting in a switching regression model with endogenous selection. Section 2 presents the structural modeling of the production relationship within individual firms. Section 3 describes the estimation model used. Section 4 discusses the data and section 5 the results.

2. The theoretical model

We suppose that the output Y_i we observe within a given firm i is the result of a functional relationship between a set of G observable input factors, denoted as X_{gi} $(g = 1, \ldots, G)$, as well as firm and industry specific unobserved heterogeneity (shocks). More precisely we assume that the production value observed at the firm level is determined by the relationship

$$Y_i = F(X_{1i}, ..., X_{Gi})\ h(I_i)\ v_i \tag{2.1}$$

[5] Studies using French microdata show that apprenticeship training reduces significanlty the probability of initial unemployment but has little or no effect on the wages (see Sollogoub et Ulrich, 1999). Similarly, Fougère, Goux and Maurin (1998) show that continuous training has no specific effect on the post-training wages. For a review of the results concerning the effects of different training or unemployment policies see Fougère, Kramarz and Magnac (2000).

where $F(X_{1i},...,X_{Gi})$ stands for a medium or long term production goal which is predetermined to the actual observed value of Y_i. $I_i = (I_{1i}, \ldots, I_{Mi})$ is an indicator function denoting whether a firm i operates in industry sector m, and v_i represents firm specific (unobserved) heterogeneity. We aim at estimating the parameters of the functional relationship $F(.)$, since this function determines the marginal productivities of input factors and consequently that of apprentices. We use two nested specifications for $F(.)$, the first being the Cobb-Douglas production relationship and the second the Translog production function.[6] The Cobb-Douglas production function is nested within the Translog production function. The latter one may be interpreted as a second order approximation of the true function around the sample. The Cobb-Douglas production is a first order approximation. We specify the industry-specific shock function as

$$h(I_i) = \exp\left(\sum\nolimits_{m=1}^{M} \alpha_m I_{mi}\right) \tag{2.2}$$

and assume that the firm-specific shocks are log-normally distributed, i.e. $v_i = \exp(u_i)$ with $u_i \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_u)$. Under these assumptions the Cobb-Douglas specification may be written as

$$\ln Y_i = \beta_0 + \sum\nolimits_{g=1}^{G} \beta_g \ln X_{gi} + \sum\nolimits_{m=1}^{1} \alpha_m I_{mi} + u_i \tag{2.3}$$

whereas the Translog specification yields the following relationship

$$\begin{aligned} \ln Y_i \quad = \quad & \beta_0 + \sum\nolimits_{g=1}^{G} \beta_g \ln X_{gi} \\ & +0.5 \sum\nolimits_{g=1}^{G} \sum\nolimits_{g'=1}^{G} \beta_{gg'} \left(\ln X_{gi} - \overline{\ln X_g}\right)(\ln X_{g'i} - \overline{\ln X_{g'}}) \\ & + \sum\nolimits_{m=1}^{M} \alpha_m I_{mi} + u_i, \quad with\ \beta_{gg'} = \beta_{g'g}\ \forall\, (g, g') \end{aligned} \tag{2.4}$$

$\overline{\ln X_g}$ being the mean of the logarithm of input factor g in the sample. Among input factors we distinguish four types of workers: Apprentices, whose number is A_i in firm i, skilled workers, whose number is S_i, unskilled workers whose number is U_i, and the other employees/workers which are not part of one of the abovementioned categories, denoted E_i. Concerning capital we observe the true capitalization level for French firms, but only an approximation for German firms (investment). In order to make the datasets comparable, we identify four capitalization levels for both countries K_i.[7] The marginal productivity of apprentices with firm i, denoted as MPA_i, is then

$$MPA_i = \frac{\partial \ln Y_i}{\partial \ln A_i} \times \frac{Y_i}{A_i}$$

[6] See Christensen et al. (1971, 1973).

[7] The capitalisation levels for German firms are calculated using the overall value of investments in the actual time period. The tresholds between these levels are determined using the capitalisation distribution of French firms conditioned on their size category and industry sector.

with

$$\partial \ln Y_i / \partial \ln A_i = \beta_A$$

for the Cobb-Douglas specification, and

$$\partial \ln Y_i / \partial \ln A_i = \beta_A + \sum_{g=1}^{G} \beta_{Ag} (\ln X_{gi} - \overline{\ln X_g}) \left(1 - \frac{1}{N}\right)$$

for the Translog specification. Here, N denotes the number of observations in the sample.[8] Defining

$$s_g = \frac{\partial \ln Y_i}{\partial \ln X_{gi}}$$

as the share of the g-th input factor in total output, the partial substitution elasticities between factors g and g' may be written as

$$\sigma_{gg'} = \frac{s_g s_{g'}}{\beta_{gg'} + s_g s_{g'}} \tag{2.5}$$

Analogously, the own-price factor demand elasticities may be calculated as

$$\sigma_{gg} = \frac{s_g^2}{\beta_{gg} + s_g^2 - s_g}. \tag{2.6}$$

3. The econometric model

For a number of firms in both datasets we observe no apprentices ($A_i = 0$). A limitation of the estimation on the subsample of firms where we observe apprentices would lead to biased estimates of the model parameters[9] There are in fact good reasons to believe that hiring apprentices is not a purely random decision, but depends on a number of factors which characterize the anticipated returns from apprenticeship training. Let $\mathbf{Z}_i$ be the vector of variables which affect the expected return of participation in apprenticeship training for a given firm i and let I_i^* be the (to the econometrician non-observable) variable representing the expected net return from apprenticeship training for firm i. We assume that the relation between I_i^* and $\mathbf{Z}_i$ is of the following linear form:

$$I_i^* = \mathbf{Z}_i \boldsymbol{\delta} + \eta_i \tag{3.1}$$

where η_i stands for an standard normally distributed error term and $\boldsymbol{\delta}$ is a coefficient vector to be estimated. Given this formulation, the hiring of a number of apprentices by firm i corresponds to $I_i^* > 0$. In order to take this selectivity problem into account, we rewrite (2.4) as:

$$y_i = \begin{cases} y_{1i}^* = \mathbf{X}_{1i} \boldsymbol{\beta}_1 + u_{1i} & \text{si} \quad I_i^* > 0 \\ \\ y_{2i}^* = \mathbf{X}_{2i} \boldsymbol{\beta}_2 + u_{2i} & \text{si} \quad I_i^* < 0 \end{cases} \tag{3.2}$$

[8] See Hamermesh (1993) for a discussion of the Translog production technology as wells as the derivation of the formulas for the substitution and own-price elasticities based on this specification.

[9] See Heckman, 1979.

where $y_i = \ln Y_i$. The variables in $\mathbf{X}_{1i}$ are $\ln A_i$, $\ln S_i$, $\ln U_i$, $\ln E_i$ and K_i defined above as well as industry dummies. $\mathbf{X}_{2i}$ contains the same variables except for $\ln A_i$ and the interaction terms including $\ln A_i$ in (2.4). Except for the industry dummies the variables in $\mathbf{Z}_i$ are different from those in $\mathbf{X}_{1i}$ and $\mathbf{X}_{2i}$. We further assume that the error terms of (3.2) and (3.1) follow the multivariate distribution

$$(u_{1i}, u_{2i}, \eta_i)' \sim \mathcal{N}(0, \Sigma) \quad \forall i$$

where

$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_1 & 0 & \rho_{1\eta} \\ 0 & \sigma_2 & \rho_{2\eta} \\ \rho_{1\eta} & \rho_{2\eta} & 1 \end{pmatrix}.$$

Define

$$d_i = \begin{cases} 1 & \text{si } \mathbf{Z}_i\boldsymbol{\delta} + \eta_i > 0, \\ 0 & \text{sinon.} \end{cases}$$

The parameters of the model are estimated using with maximum likelihood. The likelihood function of the model writes itself as :

$$\begin{aligned} L &= \prod_{i=1}^{N} (L_i | d_i = 1)^{d_i} \times (L_i | d_i = 0)^{1-d_i} \\ &= \prod_{i=1}^{N} \Phi \left[\left(\frac{\mathbf{Z}_i\boldsymbol{\delta} + \frac{\rho_{1\eta}}{\sigma_1}(y_i - \mathbf{X}_{1i}\boldsymbol{\beta}_1)}{\sqrt{(1-\rho_{1\eta}^2)}} \right) \times \phi \left(\frac{y_i - \mathbf{X}_{1i}\boldsymbol{\beta}_1}{\sigma_1} \right) \right]^{d_i} \\ &\quad \times \Phi \left[\left(\frac{-\mathbf{Z}_i\boldsymbol{\delta} - \frac{\rho_{2\eta}}{\sigma_2}(y_i - \mathbf{X}_{2i}\boldsymbol{\beta}_2)}{\sqrt{(1-\rho_{2\eta}^2)}} \right) \times \phi \left(\frac{y_i - \mathbf{X}_{2i}\boldsymbol{\beta}_2}{\sigma_2} \right) \right]^{1-d_i} \end{aligned}$$

4. Data

In order to estimate the production function described above we use two datasets. The first contains French firm level data for 1992; it is the result of the matching of two INSEE - surveys, the *Enquête sur le Coût de la Main d'Oeuvre et sur la Structure des Salaires* (ECMOSS) and the *Enquête sur les Bénéfices Industriels et Commerciaux* (BIC). In the sample we have about 10 000 firms from all industries of the French economy .[10] The second dataset is an extraction of the IAB - firm panel (*Institut für Arbeitsmarkt- und Betriebsforschung*). It contains 4 500 firms of all industry sectors in 1993. This sample was matched to the *Historikdatei* database containing all employees being affiliated to the German social security system.[11]

[10] The comparability of the industry sectors between France and Germany was assured using three digit industry classification for the two countries.
[11] See Bellmann (1997) and Bender et al. (2000) for a description of these databases.

Although for Germany we have an overrepresentation of large firms, descriptive statistics are largely identical for the two countries (see Tables 1 to 4 in Annex A). In order to guarantee the comparability of monetary units (turnover, capital stock), we have transformed them all into German marks (DM) of 1992. For both countries we have restricted the skilled workers category to those professions which are attainable by apprenticeship graduates in the respective country; other skilled workers have been included into category E_i. The unskilled worker are defined as those whose profession does not require a specific qualification. For Germany we used the qualification classification of Blossfeld (1989). It distinguishes between five qualification levels: Agricultural and unskilled workers, skilled workers (including skilled workers, technicians and some engineer categories), unskilled employees (having easy tasks), skilled employees and managers. For our analysis we combine the unskilled workers and employees in the one hand and the skilled workers and employees on the other. For France we used the distinction between skilled and unskilled workers as defined by the codification PCS.

5. Results

We estimated the models of section 2 for four groups of firms: Small and medium sizes firms (less than 200 employees) and large firms (more than 200 employees) for each of both countries. The estimated parameters are shown in tables 5 and 6 (Annex B). They stand for elasticities of production defined as $\eta_{YX} = d\ln Y \,/\, d\ln X$. With the Translog (TL) specification being a more detailed Taylor series approximation of the unknown production relationship, we will compare only the first order terms of the TL and Cobb-Douglas (CD) specifications.

5.1. Small and medium sized firms

We start by comparing small French and German firms (less than 200 employees). In Table 5 (Annex B) we see that French firms have an estimated production elasticity of apprentices, denoted η_{YA}, of about 7% in the CD specification (no significant effect with the TL specification). Table 7 (Annex B) shows that the corresponding number for small German firms is 13% for both types of functional specifications, and therefore seems to be statistically more robust. Small French firms have a significantly higher production elasticity η_{YU} of unskilled workers when they train apprentices (Regime I) than if they do not (Regime II). As, by definition, the production elasticity is closely related to the marginal product of an input factor since $MPX = \eta_{YX} \times (X \,/\, Y)$, a higher elasticity indicates ceteris paribus a higher marginal product and, with a concave production relationship, a smaller quantity of the given input factor. So this shift suggests that firms employing apprentices do employ ceteris paribus less unskilled workers. This indicates a substitution effect which is confirmed by a quick look at Table 13 (see Appendix D), where we find an estimated substitution elasticity of about 30 % between these two groups of workers within small French firms. On the other hand, we observe a strong complementarity between apprentices and skilled workers (the substitution elasticity is -16 %) as well as a shift in the production elastictiy of skilled workers from firms employing apprentices (35% for the CD specification, 39% for the TL specification) to firms without apprentices (42% for the CD specification, 50% for the TL specification), meaning that firms with apprentices do employ more skilled workers than those without apprentices. Additionally, the substitution elasticity between unskilled and skilled workers is about 87%.

For small German firms (see Table 7, Appendix B), asides from the higher production elasticity of apprentices (13%), we find the opposite pattern for the production elasticities of unskilled and skilled workers between firms employing apprentices and those that do not. Whereas we find a significant increase of unskilled workers' production elasticity from 13% to 27% with the CD specification (from 19% to 25% with the TL specification), we estimate a significant and stable decrease of the production elasticity of skilled workers: (from 61% to 44% with the CD specification, and from 60% to 45% with the TL specification). Within small German firms (see Table 15, Appendix D), the substitution elasticity between apprentices and unskilled workers is very high (104%); however we do not find any significant correlation between the demand for apprentices and the demand for skilled workers. On the other hand, skilled and unskilled workers are complementary (their substitution elasticity is - 47%).

From these results, we conclude that small French firms employ apprentices mostly to provide themselves with skilled workers in the future. At the same time, skilled workers and apprentices substitute unskilled workers. We do not find uncontested evidence for a significant production activity of apprentices within small French firms (no significant effect using the Translog specification), whereas we do so for small German firms. In small German firms, the main function of training apprentices seems to find a cheaper substitute for unskilled workers.

5.2. Large firms

The situation with large firms is a quite different to that with small and medium sized firms (the estimation results are shown in table 6 of Annex B). First of all with large French firms the production process is not sensitive to the employment of apprentices. With large German firms the production elasticity is significant under the CD but not with the TL specification. Using the CD specification we find with large firms training apprentices a lower production elasticity of skilled workers than with large firms not training apprentices. This might be interpreted that large firms train apprentices especially if they are in need of skilled work. These results are valid for France as well as for Germany.

The substitution elasticity of apprentices and other types of workers are never significant with large firms in both countries (see tables of Annex C). However, for both countries we find identically significant substitution elasticities between skilled and unskilled workers of about 65%.

6. Conclusion

In this paper we evaluated the productivity of apprentices in Franc and Germany. The econometric analysis was based on two cross-section datasets, one of whom was constructed by matching two INSEE firm-level surveys whereas the second one is an extraction of the IAB - firm panel. We estimate Cobb-Douglas and Translog production functions combined with a probit selection equation which allows to control for the situation where a given firm does not train apprentices. Concerning the productivity of apprentices we find a structural difference between small and large firms, which is more pronounced with German firms. Especially with small German firms we find a strong involvement of apprentices in the production process. For large firms the current production argument does not seem to hold anymore in order to explain the observed behaviour. For France, the results are similar, although small and medium sized firms do use apprenticeship training more as a means of investment in human capital than small and medium sized German firms.

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Annex A: Variable descriptions[12]

Tableau 1: Moins de 200 salariés - France (11 665 observations)					
Variable	moyenne	écart type	minimum	maximum	unité
lnY	8.19	1.22	1.09	14.82	10^3 DEM(1992) / année
lnU	1.77	1.22	-3.00	5.00	nombre pondéré
lnS	2.17	1.20	-1.95	5.14	nombre pondéré
lnA	0.19	0.52	0.00	4.34	nombre absolu
lnE	1.84	1.04	0.00	5.27	E = L - S - A - U
K1	0.72	0.45	0.00	1.00	capitalisation faible
K2	0.20	0.40	0.00	1.00	capitalisation moyenne
K3	0.06	0.24	0.00	1.00	capitalisation forte
K4	0.02	0.14	0.00	1.00	capitalisation très forte

Tableau 2: Plus de 200 salariés - France (1 403 observations)					
Variable	moyenne	écart type	minimum	maximum	unité
lnY	11.12	1.43	1.52	17.98	10^3 DEM(1992) / année
lnU	4.43	1.30	-0.94	8.63	nombre pondéré
lnS	5.24	1.29	-0.67	8.76	nombre pondéré
lnA	0.70	1.14	0.00	5.62	nombre absolu
lnE	4.52	1.38	0.00	9.81	E = L - S - A - U
K1	0.39	0.49	0.00	1.00	capitalisation faible
K2	0.33	0.47	0.00	1.00	capitalisation moyenne
K3	0.17	0.38	0.00	1.00	capitalisation forte
K4	0.12	0.32	0.00	1.00	capitalisation très forte

[12] Dans les Tableaux 1 à 4, L représente le nombre total de salariés dans l'entreprise

Tableau 3: Moins de 200 salariés - Allemagne (2 157 observations)					
Variable	moyenne	écart type	minimum	maximum	unité
lnY	8.18	1.77	3.65	14.09	10^3 DEM(1992) / année
lnU	1.52	1.60	-1.39	5.65	nombre pondéré
lnS	2.01	1.53	-1.39	6.59	nombre pondéré
lnA	0.48	0.80	0.00	4.08	nombre absolu
lnE	1.26	1.10	0.00	5.02	E = L - S - A - U
K1	0.58	0.49	0.00	1.00	capitalisation faible
K2	0.15	0.36	0.00	1.00	capitalisation moyenne
K3	0.23	0.42	0.00	1.00	capitalisation forte
K4	0.04	0.19	0.00	1.00	capitalisation très forte

Tableau 4: Plus de 200 salariés - Allemagne (1 628 observations)					
Variable	moyenne	écart type	minimum	maximum	unité
lnY	12.30	1.64	1.91	18.77	10^3 DEM(1992) / année
lnU	5.40	1.36	-0.29	9.46	nombre pondéré
lnS	5.93	1.23	0.00	9.88	nombre pondéré
lnA	3.24	1.59	0.00	7.30	nombre absolu
lnE	4.04	1.99	0.00	10.19	E = L - S - A - U
K1	0.19	0.39	0.00	1.00	capitalisation faible
K2	0.17	0.37	0.00	1.00	capitalisation moyenne
K3	0.45	0.50	0.00	1.00	capitalisation forte
K4	0.19	0.39	0.00	1.00	capitalisation très forte

Annexe B: Parameter estimation[13]

Tableau 5: Firms with less than 200 employees

	Cobb Douglas				Translog			
	Germany		France		Germany		France	
Variable	Regime I	Régime II	Regime I	Regime II	Regime I	Regime II	Regime I	Regime II
lnA	0.13		0.07		0.13		0.02	
	(0.04)		(0.02)		(0.06)		(0.03)	
lnA*lnA					0.02		0.01	
					(0.03)		(0.01)	
lnU	0.13	0.27	0.27	0.19	0.19	0.25	0.26	0.21
	(0.03)	(0.03)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)
lnU*lnU					0.08	0.06	0.03	0.06
					(0.01)	(0.02)	(0.01)	(0.01)
lnS	0.61	0.44	0.35	0.42	0.60	0.45	0.39	0.50
	(0.03)	(0.03)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)
lnS*lnS					0.07	0.03	0.08	0.10
					(0.02)	(0.02)	(0.01)	(0.01)
lnE	0.15	0.19	0.26	0.31	0.06	0.15	0.25	0.27
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
lnE*lnE					0.07	0.03	0.04	0.03
					(0.02)	(0.02)	(0.01)	(0.01)
K2	1.67	0.39	0.57	0.38	1.57	0.39	0.53	0.35
	(0.14)	(0.17)	(0.06)	(0.04)	(0.15)	(0.17)	(0.06)	(0.04)
K3	1.25	0.64	0.38	-0.15	1.10	0.58	0.68	0.04
	(0.11)	(0.12)	(0.10)	(0.04)	(0.12)	(0.12)	(0.12)	(0.05)
K4	1.59	1.18	0.17	-0.05	1.29	1.17	0.23	-0.15
	(0.23)	(0.24)	(0.12)	(0.07)	(0.26)	(0.24)	(0.15)	(0.08)
Industry	+	+	+	+	+	+	+	+
Interact.					+	+	+	+
logL	-4024.79		-19605.60		-3910.73		-19026.55	
LR-Test	833.85^{**}		3712.74^{**}		130.33^{**}		3508.37^{**}	
N	978	1179	3 195	8 470	978	1179	3 195	8 470

[13] Dans les Tableaux 5 et 6, les nombres entre parenthèses représentent les écarts-types estimés des paramètres estimés. Les signes + indiquent que les variables indicatrices des secteurs d'activité et des interactions entre ces variables et les facteurs de production sont incorporées dans le modèle, bien que les estimations des paramètres correspondants ne soient pas reportées dans les tableaux.

Tableau 6: Firms with more than 200 employees

	Cobb Douglas				Translog			
	Germany		France		Germany		France	
Variable	Regime I	Regime II	Regime I	Regime II	Regime I	Regime II	Regime I	Regime II
lnA	0.07		0.04		0.06		0.19	
	(0.03)		(0.04)		(0.04)		(0.15)	
lnA*lnA					-0.01		-0.007	
					(0.01)		(0.03)	
lnU	0.21	0.11	0.05	0.06	0.24	0.53	-0.61	0.27
	(0.03)	(0.07)	(0.05)	(0.04)	(0.04)	(0.15)	(0.18)	(0.11)
lnU*lnU					0.03	0.12	0.09	0.04
					(0.02)	(0.04)	(0.04)	(0.03)
lnS	0.39	0.45	0.17	0.33	0.37	0.02	0.42	0.04
	(0.04)	(0.09)	(0.06)	(0.05)	(0.05)	(0.24)	(0.18)	(0.12)
lnS*lnS					-0.07	-0.15	-0.02	0.11
					(0.03)	(0.06)	(0.04)	(0.03)
lnE	0.12	0.12	0.20	0.22	0.17	0.14	0.43	0.63
	(0.02)	(0.05)	(0.03)	(0.04)	(0.02)	(0.09)	(0.16)	(0.12)
lnE*lnE					0.04	0.04	0.06	0.02
					(0.01)	(0.02)	(0.02)	(0.01)
K2	0.24	0.20	0.23	0.07	0.04	0.10	0.58	1.10
	(0.19)	(0.52)	(0.26)	(0.18)	(0.20)	(0.56)	(0.43)	(0.37)
K3	0.14	-0.21	-0.15	-0.26	-0.02	0.02	0.33	2.18
	(0.15)	(0.45)	(0.27)	(0.20)	(0.16)	(0.67)	(0.50)	(0.45)
K4	0.27	-0.46	0.31	0.25	0.03	-0.42	-0.24	0.55
	(0.18)	(0.59)	(0.24)	(0.18)	(0.19)	(0.75)	(0.95)	(0.47)
Industry	+	+	+	+	+	+	+	+
Interact.					+	+	+	+
logL	-2798.92		-3076.695		-2733.412		-3013.644	
LR-Test	143.92^{**}		172.74^{**}		92.28^{**}		178.69^{**}	
N	1495	133	683	720	1495	133	683	720

Annexe C: Substitution Elasticities[14]

Less than 200 employees, France (3195 observations)					More than 200 employees, France (683 observations)				
	A	U	S	E		A	U	S	E
A	-0.06				A	-0.14			
	(0.01)					(0.01)			
U	0.30	-0.39			U	-0.06	-0.53		
	(0.03)	(0.17)				(0.39)	(0.07)		
S	-16.13	0.87	-1.38		S	-1.13	0.65	-0.48	
	(11.04)	(0.01)	(0.16)			(0.68)	(0.12)	(0.02)	
E	0.36	-0.34	1.22	-0.43	E	2.25	1.08	0.55	-0.74
	(0.01)	(3.92)	(0.24)	(0.01)		(1.66)	(0.56)	(3.99)	(0.58)

Less than 200 employees, Germany (978 observations)					More than 200 employees, Germany (1495 observations)				
	A	U	S	E		A	U	S	E
A	-0.09				A	-0.06			
	(0.10)					(0.002)			
U	1.04	-0.61			U	197.3	-0.40		
	(0.51)	(0.04)				(199.6)	(0.01)		
S	0.90	-0.47	-1.71		S	0.07	0.65	-0.42	
	(1.28)	(0.68)	(1.40)			(0.06)	(0.06)	(0.29)	
E	1.83	-0.07	1.17	-0.29	E	0.02	-0.75	1.01	-0.32
	(0.27)	(0.83)	(0.62)	(0.03)		(1.01)	(0.84)	(0.01)	(0.01)

[14] Dans ces tableaux, les nombres entre parenthèses représentent les écarts-types estimés des estimations des élasticités moyennes.