Recruitment Difficulties and Firms' Characteristics:
An Analysis of French Company Data

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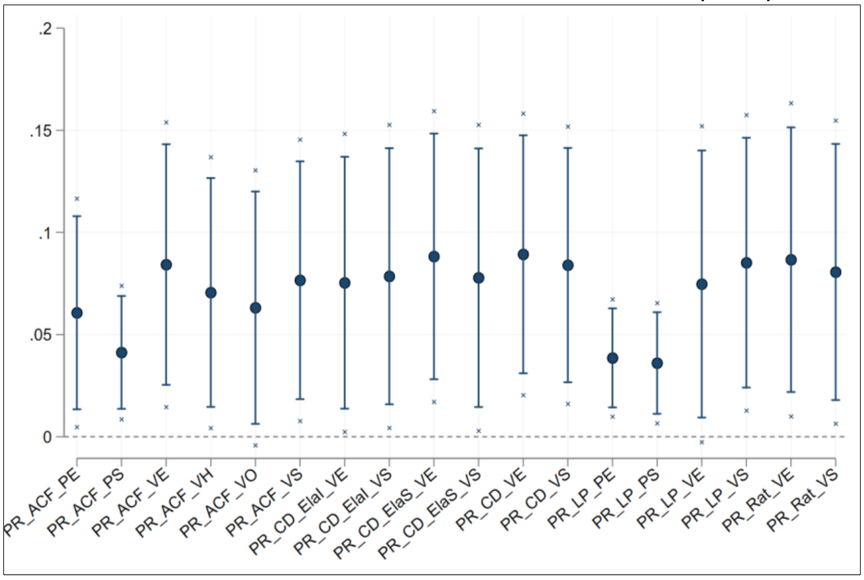
Annexe en ligne / Online Appendix

S1 – Productivity Measures and Supplementary Results

Tableau S1-1 – **Productivity measures**

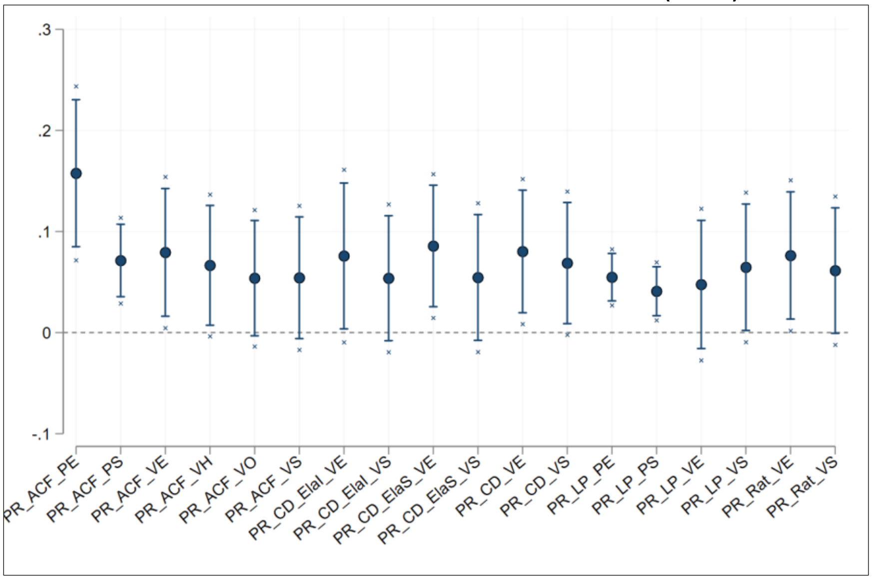
Name	**Description**
PR_Rat_VE	Ratio of value added to employment (number of employees).
PR_Rat_VS	Ratio of value added to labour cost.
PR_ACF_PE	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the number of employees and using a production approach.
PR_ACF_PS	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the total salaries and wages paid to employees and using a production approach.
PR_ACF_VE	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the number of employees and using a value added approach.
PR_ACF_VS	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the total salaries and wages paid to employees and using a value added approach.
PR_CD_ElaI_VE	Direct estimation of a Cobb-Douglas production function for value added. Labour and capital elasticities are estimated using the share of labour in the company value added, assuming constant returns to scale. Labour is measured by the number of employees.
PR_CD_ElaI_VS	Direct estimation of a Cobb-Douglas production function for value added. Labour and capital elasticities are estimated using the share of labour in the company value added, assuming constant returns to scale. Labour is measured by the total salaries and wages paid to employees.
PR_CD_ElaS_VE	Direct estimation of a Cobb-Douglas production function for value added. Labour and capital elasticities are estimated using the average share of labour in the industry's value added, assuming constant returns to scale. Labour is measured by the number of employees.
PR_CD_ElaS_VS	Direct estimation of a Cobb-Douglas production function for value added. Labour and capital elasticities are estimated using the average share of labour in the industry's value added, assuming constant returns to scale. Labour is measured by the total salaries and wages paid to employees.
PR_CD_VE	Direct estimation of a Cobb-Douglas production function for value added with labour elasticity equal to 0.7. Labour is measured by the number of employees.
PR_CD_VS	Direct estimation of a Cobb-Douglas production function for value added with labour elasticity equal to 0.7. Labour is measured by the total salaries and wages paid to employees.
PR_LP_PE	Levinsohn & Petrin (2003) method applied to a production function with labour measured by the number of employees and using a production approach
PR_LP_PS	Levinsohn & Petrin (2003) method applied to a production function with labour measured by the total salaries and wages paid to employees and using a production approach
PR_LP_VE	Levinsohn & Petrin (2003) method applied to a production function with labour measured by the number of employees and using a value added approach
PR_LP_VS	Levinsohn & Petrin (2003) method applied to a production function with labour measured by the total salaries and wages paid to employees and using a value added approach
PR_ACF_VO	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the sum of salaries and wages paid to employees and expenditure for external staff and using a value added approach
PR_ACF_VH	Ackerberg *et al.* (2015) method applied to a production function with labour measured by the total worked hours and using a value added approach

Figure S1-I – **Coefficients and confidence intervals for various productivity measures**
Coefficient 'Recruitment difficulties' from Table S1-2 (col. 3)



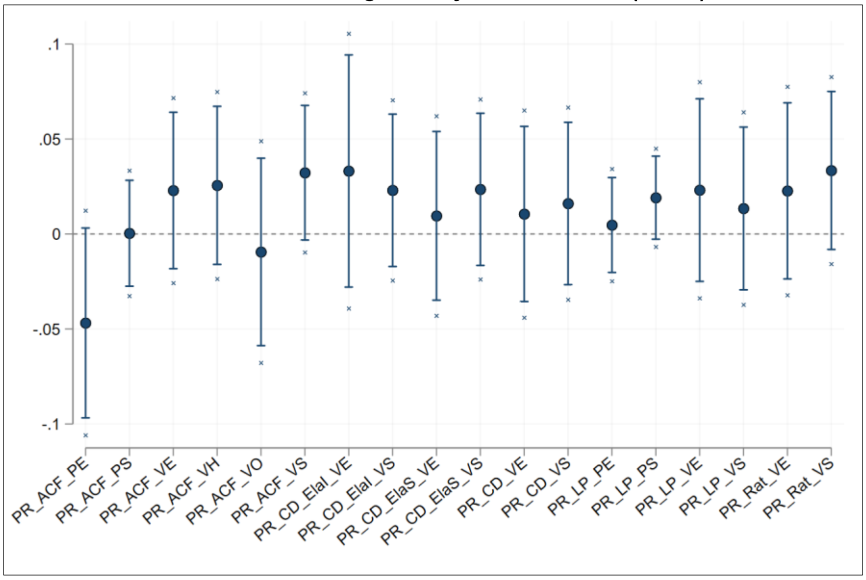
Note : each line corresponds to the estimated coefficient (estimated value represented by the dot) and the 95% (x-symbol) and 90% (vertical bar limit) confidence intervals of the coefficient. The different produvtivity measures are described in Table S1-1. The measure corresponding to Table S1-3 is PR_ACF_VS.

Figure S1-II – **Coefficients and confidence intervals for various productivity measures**
Coefficient 'Lack of labour force' from Table 4 (col. 1)



Note : cf. Figure S1-I.

Figure S1-III – **Coefficients and confidence intervals for various productivity measures**
Coefficient 'Average salary' from Table 4 (col. 1)



Note : cf. Figure S1-I.

Tableau S1-2 – **TFP and recruitment difficulties – including *département* fixed effects**

	(1)	(2)	(3)	(4)	(5)
TFP in 2018 (log)	0.703***	0.685***	0.679***	0.678***	
	(0.069)	(0.067)	(0.068)	(0.069)	
Recruitment difficulties	0.067*	0.067*	0.070**	0.073**	0.103*
	(0.036)	(0.035)	(0.035)	(0.035)	(0.061)
Employment in 2018 (log)		−0.008	−0.010	−0.012*	−0.021*
		(0.007)	(0.006)	(0.007)	(0.012)
Average salary in 2018 (log)		0.204***	0.202***	0.185***	0.330***
		(0.046)	(0.046)	(0.046)	(0.085)
Average hours (log)			0.138**	0.135**	0.261***
			(0.056)	(0.056)	(0.086)
PCU				−0.075	0.040
				(0.078)	(0.126)
RatOut				0.098**	0.112
				(0.048)	(0.079)
Adjusted R2	0.731	0.742	0.745	0.746	0.423
Number of observations	928	928	928	926	940

The standard errors given in brackets are estimated allowing an autocorrelation within the same sector of activity in the same department. ***, ** and * indicate a p-value of below 1%, 5% and 10%, respectively.
Note : Each column corresponds to an OLS regression of model (1) where the dependent variable is the TFP level (in log) calculated in 2019. Each line corresponds to an explanatory variable. The 'Recruitment difficulty' variable equals 1 if the company states that it has positions that are difficult to fill. The model includes a sector-based fixed effect (NAF code, level 2) and is weighted by using the weightings in the survey (cf. Section 3).

Tableau S1-3 – **Regression on the measures of profitabillity – reason 'Competition'**

Dependent variable	*markups*	*MR*	*ERR*	*FRR*	*GRR*
	(1)	(2)	(3)	(4)	(5)
Dependent variable in 2018	0.835***	0.831***	0.817***	0.686***	0.809***
	(0.050)	(0.040)	(0.039)	(0.061)	(0.059)
Employment in 2018 (log)	0.012	0.001	−0.000	0.001	0.002
	(0.010)	(0.005)	(0.003)	(0.003)	(0.002)
Average salary in 2018 (log)	0.130*	0.068**	0.043*	0.033**	0.026*
	(0.067)	(0.035)	(0.023)	(0.016)	(0.014)
Average hours (log)	0.267	0.086	0.084	0.097*	0.060
	(0.176)	(0.067)	(0.063)	(0.051)	(0.044)
PCU	−0.013	−0.001	0.005	−0.007	−0.008
	(0.079)	(0.037)	(0.026)	(0.024)	(0.020)
RatOut	0.276***	0.121***	0.108***	0.089***	0.074***
	(0.094)	(0.037)	(0.034)	(0.027)	(0.024)
Recruitment difficulties related to competition	−0.083**	−0.030**	−0.042***	−0.028**	−0.029***
	(0.038)	(0.015)	(0.014)	(0.011)	(0.010)
Adjusted R2	0.757	0.746	0.709	0.601	0.684
Number of observations	927	927	927	927	927

The standard errors given in brackets are estimated allowing an autocorrelation within the same sector of activity in the same department. ***, ** and * indicate a p-value of below 1%, 5% and 10%, respectively. The model is that estimated in Table S1-2 column 3.
Note : cf. Table S1-2.

S2 – The Ackerberg-Caves-Frazer (ACF) Method

Productivity is difficult to measure at company level, because of a range of well-known econometric issues: endogeneity of the quantity of input, selection bias, measurement errors, etc. (Grilliches & Mairesse, 1995). In the literature, progress in estimating company productivity has then focused on the improvement of estimation methods in order to limit the impact of these biases.

Two famous articles, Olley & Pakes (1996) [OP] and Levinsohn & Petrin (2003) [LP], have proposed two approaches based on an instrumentation of company productivity, to circumvent the problem of correlation between unobserved shocks affecting the firm's productivity and its input choices. However, Ackerberg et al (2015) show that this procedure relies on strong assumptions about the generating process of implicit data and in particular the timing of the firm's choice of employment value relative to other inputs. They therefore propose an alternative method (ACF) that is more flexible and general. Their procedure, which we describe below, is based on a two-step estimation in which the coefficient associated with labour, like that associated with capital, is obtained in the second step (while for OP and LP, labour is considered an independent variable of the implicit function governing the choice of investment and intermediate consumption values and is estimated in the first step).

The model

The ACF method considers the following production function:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}$$
$$y_{it} = \beta_\omega w_{it} + \Phi_t(s_{it}, d_{it}) + \varepsilon_{it}$$

with y_{it} the value added of company i at time t, l_{it} the labour factor for company i at time t, k_{it} the capital for company i at time t, ω_{it} an unobservable factor of state for company i at time t which affects its decisions for the production level and choice of inputs; ε_{it} represents an exogenous shock identically distributed on the production. Φ is an unspecified function which captures the changes in investment independently from I.

The model rests on three assumptions:

Chronology of the entry of factors of production into the production process
l_{it} and k_{it} are potentially endogenous since the choice of production factors (labour and capitall) depend from ω_{it}. The OP, LP et ACF methods differ in their approach to the substitution variable ω_{it}. OP uses the investment, while LP uses the intermediate production. In both cases, this implies an assumption about the timing of the production process, whereas in the ACF method, the more general assumption being:

$$k_{it} = \kappa(k_{it-1}, I_{it-1})$$

where I_{it-1} represents firm's i investment at time t decided at time t–1. This implies that the labour factor l_{it} has a dynamic dimension and can potentially be chosen at several moments: t, t–1 or t–b (with $0 < b < 1$). The ACF method is then more flexible in this aspect of chronology than the methods OP et LP.

Demand for intermediate consumption
The firm's demand for intermediate inputs m in the production process is given by:

$$m_{it} = \tilde{f}_t(k_{it}, l_{it}, \omega_{it})$$

Strict monotonicity
The demand for intermediate inputs of the firm with the production function $\tilde{f}_t(k_{it}, l_{it}, \omega_{it})$ is assumed strictly increasing in the substitution variable ω_{it}. Based on these assumptions, it is possible to reverse the demand for intermediate inputs and use it to substitute the state variable in the value added production function.
Formally, the first step of the procedure consists in regressing y on I, k and m in order to obtain an estimation of the function Φ. The second step is based on the stochastic process of ω which is assumed to follow a Markov process with exogenous parameters. Using the results from step one, hence the estimation of Φ, the identification of β_l and β_k can then be made using the condition:
$E(X|\beta_l, \beta_k|k, l) = 0$

References

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