Innovation and training: a dynamic count data model

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Abstract : This paper explores the relationship between innovation and vocational training. We consider a linear feedback model to explain the dynamics of count data processes relative to patenting activities, R&D and training expenditures. Estimations are made on a panel data set relative to French industrial firms over the period 1986-1992. Our results indicate that the vocational training have a positive impact on the technological innovation.

Keywords : count panel data, linear feedback model, patents, R&D, training.

JEL Classification: C23, C25, J24, L60, O31.

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Introduction

Human capital is considered as one of the main inputs in economic growth. It can be defined as knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity (OECD, 2005). Human capital can then generate endogenous growth thanks to a continuous process of knowledge and externalities accumulation (Aghion and Howitt, 1998). Generally considered in the theoretical models as the results of education training, human capital accumulation is actually a more complex process. First, school is neither an exclusive nor a sufficient method to train people (Mincer, 1993). It constitutes the first step, which would be completed by informal learning process linked to experiences and formal learning process such as vocational training. If the human capital theory considers that firms do not have interest to invest in vocational training, as it only advantages employees (Becker, 1962), more recent studies demonstrate that training benefits firms through direct payments or weaker wages (Booth and Bryan, 2002; Bishop, 1996). Empirical studies show that human capital, and its part acquired thanks to training, have a positive impact on labour productivity and increase firms profits (Bartel, 1989, bartel, 1994; Carriou and Jeger, 1997). Firms then expect from training gains in efficiency and a better adaptation to technical evolutions. Vocational training becomes then an investment in the same manner as R&D. In that context, some economists try to measure the effect of training on firms' other activities. Thus, human capital contributes also to innovation (REF). We can suppose then that a firm should increase its vocational training to increase the probability to innovate. However, very few empirical studies (REF) estimate the relationship between vocational training and innovation while they are inextricably linked. They show, nevertheless, a positive impact of vocational training on innovation. More studies are required to confirm these results. The aim of this paper is then to investigate the relationship between innovation and vocational training in France. Our methodological approach allows to contribute to the literature in three manners. First, we build a panel with a long times data series. This deals with the issue of non-random selection and potentially with measurement error from short panels. Second, we explicitly allow for endogeneity[1] and fixed effects using GMM techniques. Finally, we are able to propose different indicators of vocational training.

Our data come from the French fiscal declarations concerning the firms' vocational training annual expenditures, the INPI database on patents[2] and the R&D survey issued from the French Ministry of research. The three databases cover the period 1986-1992. The sample of the firms used comprises 321 firms. The originality of our database is to allow to build different indicators of training and to have dynamic analysis.

This article is organized as follows. In the next section, we analyse the literature on the linkage between the vocational training and innovation. The data and the definition of variables are presented in section 2. The econometric specification of the model is examined in section 3. The main results are discussed in section 4.

1 Training and innovation

Technological progress does not occur instantaneously or by chance but results from goal-oriented investment in human capital and R&D. Individuals and firms make decisions about innovation, R&D and investment in human capital. Development and diffusion of knowledge are crucial sources of growth, whereas human capital investment is the most important input for the advance of science and knowledge. This idea developed by Nelson and Phelps (1966) has been taken up by the economists of the endogenous growth as Aghion and Howitt (1998) in the schumpeterian growth models.

[1] This was a problem in the Lynch's 1995 and 1996 papers.

[2] Institut National de la Propriété industrielle/French National industrial property office.

In opposition to the standard concept of the human capital, which considers that human capital is only another factor to take into account to measure the economic growth (Benhabib and Spiegel, 1994), Nelson and Phelps (1966) model for the first time, the idea that education leads to increase the capacity to innovate (creation of activities, products and technologies) and to adopt new technologies. They consider that "*education enhances the ability to receive, decode, and understand information*", (Nelson and Phelps, 1966, page 69). The interesting and innovative results of this approach rise from the close link it establishes between technical progress and education. One of the first conclusions of Nelson and Phelps, which is empirically verifiable, is that the growth rates of productivity and innovations are positively correlated with the level of education, in particular with the number of persons which have high school or university diploma.

The technological innovation develops the capacities of the firms because it encourages them to invest regularly in human capital and to accumulate competencies. Moreover, the regular introduction of the technological innovations increases the capacity of training and of absorption of the employees. This concept of absorptive capacity, developed by Cohen and Levinthal (1990), is now regarded as a key element of technological progress of firms. According to these authors, the learning capacity of firms depends on their internal capacities that can be measured by the number of researchers which are present in the R&D department. Following Ballot, Fakhfakh and Taymaz, (1998, 2001a, 2001b), we consider that this measure is not sufficient and we insist on the role of vocational training, in the absorptive capacity.

However, there are few empirical studies on this subject. Lynch and Black (1994) show that in United States, the ratio of educated employees is positively correlated to R&D activities. In the same way, from a sample of only 200 big firms, Ballot, Fakhfakh and Taymaz (1998) calculate a training stock of the firm, in cumulating training expenditures from 1987 to 1993. They test a production function in which they include possible interactions between human capital and R&D. They conclude that vocational training and R&D are significant factors of production function. The main limits of this model are the small size of the sample and the absence of longitudinal data which would allow to control the unobserved and specific characteristics of firms. More recently, Ballot et al. (2001) find a positive effect of continuous training on probability to innovate for the French firms. They explain the probability to innovate among others variables by a R&D indicator and a human capital variable measured by a depreciated stock of continuous training expenditures. However, the authors do not distinguish firms which are effectively engaged in training from those which only pay the tax corresponding to the French legal obligation[3]. The absence of the differentiation of these two “training models”leads to suppose that every firm actively trains one part of these employees. It can imply an over-estimation of training effect on R&D. These models propose interesting results but need to be completed. In that purpose, we propose to estimate a knowledge production function in which we introduce vocational training in distinguishing the effective expenditures from the tax expenditures and we test panel data.

2 The model

Traditionally, the relationship between innovation and R&D is interpreted as a knowledge production function describing the production of innovation, measured by the number of patents, and past and current R&D investments. Following Blundell, Griffith and Van Reenen (1995) and Blundell, Griffith and Windmeijer (2002) a simple way to write this relationship is:

$$Q_{it} = g\left(R_{it}, R_{it-1}, \ldots, \beta, v_i\right) \tag{1}$$

where Q_{it} is a latent measure of the firm's technological level i at the time t,

[3] In France, there is a legal obligation to have training expenditures. Firms have the choice to really invest in training or to pay a tax to the government.

R_{it} is the R&D investment, β is the vector of unknown parameters and v_i is the firm's patent propensity. We assume that the number of patents is a measure of the technological level of the firm with some error measures of the technological level of the firm i at the date t.

$$P_{it} = Q_{it} + \varepsilon_{it} \tag{2}$$

with $E\left(\varepsilon_{it} | R_{it,} R_{it-1}, \ldots, \beta, v_i\right) = 0$. Blundell, Griffith and Van Reenen (1995) and Blundell, Griffith and Windmeijer (2002) suppose that historic R&D investments are combined through a Cobb-Douglas technology to produce knowledge stock and they assume that R&D depreciates at the rate δ.

Therefore equation (2) becomes:

$$P_{it} = \left(\sum_{k=0}^{\infty} (1-\delta)^k R_{it-k}^{\beta} \right) v_i + \varepsilon_{it} \tag{3}$$

Setting $\beta < 1$ allows for a decreasing return within the investment period. By inverting the relation(3), we have:

$$P_{it} = (1-\delta) P_{it-1} + R_{it}^{\beta} v_i + \mu_{it} \tag{4}$$

with $\mu_{it} = \varepsilon_{it} - (1-\delta)\varepsilon_{it-1}$ and where $E\left(\mu_{it} | R_{it}, P_{it-1}, v_i\right) = 0$.

In this model, the conditional mean of the count data variable is modelled linearly in the history of the process. This specification is shown to be well adapted to economic applications and especially convenient for understanding the dynamic properties of count data processes. In equation (3), the only explanatory variable for patents of firm i are the current and past R&D investments of firm i.

Following Ballot at al. (2001), we assume that a firm produce innovations using two sources of knowledge. The first one is, as usual, the R&D investment and the second one is the training investment. Moreover, unlike Blundell, Griffith and Van Reenen (1995), Blundell, Griffith and Windmeijer (2002), we assume that only past R&D and past training explain the probability to innovate. So we can write:

$$P_{it} = \left(\sum_{k=1}^{\infty} (1-\delta)^k R_{it-k}^{\beta} + \sum_{k=1}^{\infty} (1-\delta)^k T_{it-k}^{\lambda} \right) v_i + \varepsilon_{it} \tag{5}$$

where training investment depreciates exponentially at the same rate δ as R&D investment[4]. So innovation of firm i depends on the elasticity β of patents P_{it} to R&D investments R_{it} and elasticity λ of patents to training investments. Inverting equation (5), we have:

$$P_{it} = (1-\delta) P_{it-1} + R_{it-1}^{\beta} v_i + T_{it-1}^{\lambda} v_i + \mu_{it} \tag{6}$$

with $\mu_{it} = \varepsilon_{it} - (1-\delta)\varepsilon_{it-1}$ and where $E(\mu_{it}|R_{it}, T_{it}, P_{it-1}, v_i) = 0$.

In count data models, where a non-linearity is produced by the non-negative discrete nature of the data, the standard generalized method of moments (GMM) for the estimation of fixed effects models is not directly applicable. The usual panel data estimator for count models with correlated fixed effects is the Poisson conditional maximum likelihood estimator proposed by Hausman, Hall et Griliches (1984). This estimator is the same as the Poisson maximum likelihood estimator in a model with specific constants. But this estimator is inconsistent if the regressors are predetermined and so not strictly exogenous. To solve this problem, Chamberlain (1992) and Wooldridge (1997) have developed a quasi-differenced GMM estimator. Blundell, Griffith and Windmeijer (2002) have extended this estimator to dynamic linear models. Following Blundell, Griffith and Windmeijer (2002), we will estimate the equation (6) with this quasi-differenced GMM estimator (see appendix for technical details).

[4]We make the hypothesis that as training investment is knowledge investment, it depreciate as R&D investment does

3 Data and variables

In order to build our sample, we use three sources of informations. The first one is the fiscal declarations 24-83 concerning the firms' vocational training annual expenditures. These data come from the CEREQ[5]. The second one is the number of patents granted by firms. These data come from the French Patent Office (INPI[6]). The last one is the French annual firm research expenditures survey. This survey is carried out by the Ministry of Research. It concerns the internal expenditure of research, that is to say R&D executed by the firm itself. It focuses on all the firms (having more than 20 employees) which carry out some R&D and employ at least one full time researcher. These three data bases cover the period 1986-1992.

Since the founder law of 1971, the firms fiscal annual declarations (n° 24-83), is the oldest element and most regular in the statistical production on the continuous vocational training in France. This source allows to provide indicators on firms'training expenditures[7], physical volumes of training and their main characteristics: training plan, part time training, duration of training, average unit cost. They are produced by classes of sizes, according to five socio-professional categories and by sector.

We constructed three measures of total vocational training volume: (1) the access rate to training; (2) the number of training hours per employee; and (3) the training expenditure per employee. These variables are the effective measures of training, that means, they take into account the training really organised by firms, and do not include tax payment, as a substitute to training, corresponding to the French legal obligation, contrary to Ballot et al. (2001). Moreover, these different measures allow to control the impact of training. In-

[5]CEREQ is a public organisation working under the aegis of both the Ministry for National Education, Higher Education and Research and the Ministry for Employment, Social Cohesion and Housing. As a centre of public expertise at the service of key players in training and employment, Céreq is involved in the production of statistics, in research activity and in providing support for the implementation of policies.

[6]Institut National de la Propriété Intellectuelle.

[7]Since 1993 the official rate reach 1,5 % of the wages for firms with 10 or more employees.

deed, if we obtain similar results with these three variables, then training would really have an impact on innovation.

Moreover, we include in our model, the distribution of employees by occupational categories in order to take into account the employee structure of the firm. This partly reflects the level of competences inside the firm. We only kept five main categories: engineers and executives, skilled workers, unskilled workers, clerks, technicians and supervisor. Each one is introduced in the model as the share of workers of one category on the total number of employees in the firm (average over the year). The variables are transformed in logarithm. The market share is computed as the ratio of firm's turnover to the total turnover of the sector on a two-digit-level (NAP[8] level 40). The size of the firm is measured by the number of employees inside the firm. These two variables are built on the model of Crépon et al. (1998).

The output of innovation is measured by the number of patents at the date t. The patent numbers come from the INPI database. Since the firm ID SIREN codes were not available in this data base, it has been necessary to carefully match SIREN code and firm names[9]. The patent variable is the total numbers of patents granted by the firm i during the period 1975-1992. We have considered the number of patents granted because it is often viewed as a more appropriate measure of innovation output.

The measurement of the innovating activity by the number of patents have some problems. Its principal defects are well-known (Levin, Klevorick, Nelson and Winter, 1987; Griliches, 1990) . First, the number of patents of a firm does not reflect the exact number of innovations carried out by the firm. Indeed, all innovations are not patented. The decision to patent varies from one firm to another. Some firms prefer not to patent because this step implies the disclosure of strategic technical information [10]. In this case, the secret can be a more effective

[8]Nomenclature des Activités et Produits.

[9]This work has been performed at ERMES by J.-D. Roebben, with the collaboration of INPI.

[10]According to Duguet and Kabla (1998) , only 30 % innovations are patented in France.

means of protection. Furthermore, the use of patent as a measure of innovation leads to give the same weight to all innovations. Counting the patents rests on the implicit assumption that each patent has the same weight that innovation was radical or incremental. Concerning the French annual firm research expenditures, we retain the information on the firm total R&D expenditures. Our sample comprises 321 manufacturing firms present during the period 1986-1992.

Results

In this section, the link between training, innovation is analyzed using the panel data sets of CEREQ, INPI and the Ministry of research. We report three estimates from a model that explore the relationship between innovation and training, according to different measures of training. The interest of these measures is that they allow to evaluate the training impact in different manner. The first one measure the intensity of training inside the firms, in measuring the number of employees that do training. The second one measure the time spent training. The last one relates to training expenditure. To have three indicators of training gives more robustness to our results. Our results are presented in tables 6, 7, 8 (pages 20 to 22). The Sargan test is always rejected. That proves the quality of our estimations. We present the result for the first estimate with the training intensity indicator measured by the number of employees trained. In a second time, we compare these results with the two other estimates. The role of training on innovation is confirmed.

Results show that past R&D expenditures have a significant and positive impact on innovation production. This result confirms the numerous models on knowledge production. The more a firm invests in R&D, the more it patents. Conversely, the number of patents obtained into $(T-1)$ decreases the probability to innovate in period t[11]. There would be a lack of persistence of innovation.

[11] Several estimations were done with lagged patents variables in $t-2$, $t-3$.... These lagged patents do not act on patent production.

Our results confirm the ones of Raymond et al. (2006). They show that once the individual effects and the initial conditions are allowed for, they seem to take over the role of persistence, measured with lagged patent variable. But they also put in evidence that there is a persistent effect in engaging in R&D activities, that means when they test R&D inputs rather than output measures.

More interesting is that the training rate has a positive and significant effect on innovation production. Our results confirm our hypothesis that training influence innovation. The structure of qualifications takes part too in the explanation of the innovation. These results seem to show that innovation passes by all the workers of the firm. Executives and engineers have the higher impact, then the skilled workers and finally the unskilled workers.

The size of the firm, measured by the number of employees, does not have a significant impact. This result confirms the recent studies showing that even if the size of the companies plays a significant part in models applied to the sources of innovation (such as R&D), the relation between the size of the firms and their performances such as innovation is often no significant or negative[12] (Mohnen and Therrien, 2002; Lööf and Heshmati, 2002; Seersucker, Duguet and Mairesse, 1998, 2000). Let us note, all the same, that Duguet and Greenan (1997) finds an effect positive of the size company, measured by the firm's production in volume, on the innovation. Additional regressions carried out show that the size does not affect the probability to innovate when it is measured by the sales when the sectoral dummies are introduced or not.

The most the market share is high, the less firm innovate. This result runs counter the schumpeterian assumption. Schumpeter believed that technological innovations are more likely to be initiated by large rather small firms. This theory can be studied from two different perspectives depending on whether absolute or relative size is emphasized (Rosenberg, 1976).

The first model shows the role of training in innovation process. We now

[12] Seersucker, Duguet and Mairesse (1998, 2000) regress the number of patents divided by sales.

compare the results of our first model with the two other ones. The only difference between these models is the measure of training. When training is measured by the number of hours spent training the results are very similar to the first model. The main differences are that lagged patent variable is not anymore significant and that technicians and supervisors variable is. There would not have a persistent innovation effect.

In the third model, the results are more sensibly different. The training variable measured by training expenditures is still positive and significant. Its coefficient is much higher than in the two previous models. That would show that training is important but the level of expenditures dedicated to training is more crucial for innovation. The share of executives and engineers is not anymore significant. A possible explanation is that training is mainly destined to executive, and then the impact observed before is absorbed now by training expenditures. Technician and executive?

Conclusion

Recently the focus of empirical innovation research has changed from innovation input to innovation output. In this paper we analyze empirically the link between the input to the innovation process and the output in French manufacturing firms. The following conclusions can be drawn: The estimations with different measures of training confirm the impact of training in innovation process. They also put in evidence that if it is important that many workers benefit from training, the more important for firm performance is the level of expenditures that dedicates to these activities. Further works could study the impact of training according occupational categories in order to test our hypothesis which supposes that executive would benefit from more training than other categories.

References

AGHION, P., AND P. HOWITT (1998): *Endogenous growth theory*. Cambrige, Mass.: MIT Press.

BALLOT, G., F. FAKHFAKH, AND E. TAYMAZ (1998): "Formation continue, Recherche et développement et performance des entreprises," *Formation et Emploi*, (64), 43–58.

——— (2001a): "Firms' Human Capital, R&D and Performance: A Study on French and Swedish Firms," *Labour Economics*, 8(64), 443–462.

——— (2001b): "Who benefits from training and R&D: The firm or the workers? A study on panels of French and Swedish firms," Discussion paper, ERMES.

CRÉPON, B., E. DUGUET, AND I. KABLA (1996): "Schumpeterian conjectures: a moderate support from various innovation measures," in *Determinants of innovation: the message from new indicators*, ed. by Kleinknecht. Mc Millan.

CRÉPON, B., E. DUGUET, AND J. MAIRESSE (1998): "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level," *Economics of Innovation and New Technology*, 7(2), 115–158.

——— (2000): "Mesurer le rendement de l'innovation," *Economie et Statistique*, 334(4), 65–78.

DUGUET, E., AND N. GREENAN (1997): "Le biais technologique: Une analyse econometrique sur donnees individuelles," *Revue Economique*, 48(5), 1061–89.

GRILICHES, Z. (1990): "Patent Statistics as Economic Indicators: a Survey," *Journal of Economic Literature*, 28(1), 1661–1707.

LEVIN, R. C., A. K. KLEVORICK, R. R. NELSON, AND S. G. WINTER (1987): "Appropriate the Returns from Industrial R&D," *Brookings Papers on Economic Activity*, 3(3), 783–820.

LÖÖF, H., AND A. HESHMATI (2002): "Knowledge capital and performance heterogeneity: A firm-level innovation study," *International Journal of Production Economics*, 70(3), 61–85.

MOHNEN, P., AND P. THERRIEN (2002): "How Innovative are Canadian Firms Compared to Some European Firms? A Comparative Look at Innovation Surveys," *Technovation*, (3), 231–254.

NELSON, R. R., AND E. PHELPS (1966): "Investment in Humans, Technological Diffusion, and Economic Growth," *The American Economic Review*, 2(3), 69–75.

ROSENBERG, J. B. (1976): "Research and Market Share: A Reappraisal of the Schumpeter Hypothesis," *The Journal of Industrial Economics*, XXV(2), 101–112.

WLADIMIR, R., P. MOHNEN, F. PALMX, F. PALM, AND S. S. VAN DER LOEFF (2006): "Persistence of Innovation in Dutch Manufacturing: Is it Spurious?," .

Table 1: Summary statistic for patents

Year	Means of patents granted	Standard error	Minimum	Maximum
All years	5.07	16.63	0	188
1986	4.12	12.16	0	108
1987	4.44	12.53	0	101
1988	5.13	16.89	0	161
1989	5.28	17.30	0	181
1990	5.46	17.85	0	188
1991	5.62	18.37	0	182
1992	5.62	19.37	0	187
Observations: 321				
Sources: Ministère de la Recherche, INPI, CEREQ				

Table 2: Summary statistic for training expenditures per employee

Year	Mean	Standard error	Minimum	Maximum
All years	4 160.88	3 365.15	305.92	30 313.27
1986	2 662.36	2 544.86	305.92	25 731.65
1987	3 029.75	2 625.83	328.10	23 517.84
1988	3 397.15	2 706.8	350.28	21 304.03
1989	3 864.50	2 930.12	385.25	22 615.59
1990	4 391.70	3 286.76	527.20	24 355.63
1991	4 709.57	3 545.54	757.12	30 313.27
1992	5 027.19	3 610.12	591.12	30 056.31

Observations: 321

Sources: Ministère de la Recherche, INPI, CEREQ

Table 3: Summary statistic for access rate to training

Year	Mean	Standard error	Minimum	Maximum
All years	34.5280561	22.2823273	0	187.0078740
1986	26.5740360	18.3500191	0	128.1079442
1987	29.6550831	20.7906414	0	120.4943949
1988	32.5120412	21.4207690	0	114.6821844
1989	35.5762503	21.5358836	0	116.0753077
1990	38.0904347	23.5706124	0	187.0078740
1991	39.3022880	23.9442737	0	137.6299376
1992	39.9387878	22.5005196	0	100.0000000

Observations: 321

Sources: Ministère de la Recherche, INPI, CEREQ

Table 4: Summary statistic for number of training hours

Year	Mean	Standard error	Minimum	Maximum
All years	15.9851566	15.1612535	0	397.3169643
1986	12.3688683	11.0061379	0	94.5688175
1987	13.1244580	10.7139869	0	77.3004115
1988	15.7960027	24.1963159	0	397.3169643
1989	16.4278903	12.2574746	0	76.4483004
1990	17.7812078	15.2447205	0	165.8550725
1991	18.2420912	14.5121000	0	138.3083333
1992	18.1371905	12.8499526	0	69.2458159

Observations: 321
Sources: Ministère de la Recherche, INPI, CEREQ

Table 5: Summary statistic for explanatory variables

Variable	Mean	Standard error	Minimum	Maximum
R&D*	21.4080	44.02	0	469.87
Size	2 745.41	9 235.24	10	124 346
Market share (%)	0.0023	0.006	$5.20.10^{-6}$	0.0878
Employees (%)	0.1890	0.2099	0	1.0000
Unskilled workers (%)	0.3568	0.1956	0	0.9162
Skilled workers (%)	0.1442	0.1063	0	1.0000
Executive and engineers (%)	0.1833	0.1126	0	0.7066
Technicians and supervisor (%)	0.1261	0.0943	0	0.6893
Observations: 321				
Sources: Ministère de la Recherche, INPI, CEREQ				

*: Thousands of Francs

Table 6: GMM Results specification 1

Variables	Coefficients	Std. err.	T. Stat
Number of patents $(t-1)$	-0.0275	0.0136	-2.0183
R&D $(t-1)$	0.2164	0.0202	10.7355
Access rate to training $(t-1)$ (log)	0.0763	0.0111	6.8891
Market share $(t-1)$ (log)	-0.1170	0.0147	-7.9688
Size $(t-1)$ (log)	-0.0915	0.0526	-1.7383
Clerks	ref.	ref.	ref.
Unskilled workers $(t-1)$ (log)	0.0351	0.0043	8.0935
Skilled workers $(t-1)$ (log)	0.1357	0.0158	8.5989
Executive and engineers $(t-1)$ (log)	0.5572	0.0373	14.9424
Technicians and supervisor $(t-1)$ (log)	0.0282	0.0216	1.3077
Sargan test χ^2 (df) (p-value)	133.3488	141	0.6643
1st order serial correlation (p-value)	0.6376	0.5237	
2st order serial correlation p-value)	-1.4100	0.1586	
Observations : 321			
Sources: Ministère de la Recherche, INPI, CEREQ			

GMM is a quasi-differenced GMM using the Chamberlain (1992) decomposition.

Instruments are $y_{t-3}, \dots, y_{t-6}, x_{it-2}, \dots, x_{it-6}$.

Standard errors are the two step GMM standard errors. Sargan test is the standard χ^2 test for overidentifying restrictions.

1st and 2nd order serial correlations are the tests for no serial correlations first and second order correlations of the residuals.

Table 7: GMM Results specification 2

Variables	Coefficients	Std. err.	T. Stat
Number of patents $(t-1)$	-0.0036	0.0139	-0.2561
R&D $(t-1)$ (log)	0.2296	0.0187	12.2495
Number of training hours per employee $(t-1)$ (log)	0.0838	0.0129	6.5076
Market share $(t-1)$ (log)	-0.1063	0.0175	-6.0648
Size $(t-1)$ (log)	-0.1510	0.0573	-2.6352
Clerks	ref.	ref.	ref.
Unskilled workers $(t-1)$ (log)	0.0349	0.0044	7.9060
Skilled workers $(t-1)$ (log)	0.1315	0.0152	8.6603
Executive and engineers $(t-1)$ (log)	0.5116	0.0373	13.7329
Technicians and supervisor $(t-1)$ (log)	0.0527	0.0241	2.1886
Sargan test χ^2 (df) (p-value)	132.2976	141	0.6877
1st order serial correlation (p-value)	0.17976	0.8574	
2st order serial correlation (p-value)	-1.2599	0.2077	
Observations : 321			
Sources: Ministère de la Recherche, INPI, CEREQ			

GMM is a quasi-differenced GMM using the Chamberlain (1992) decomposition.

Instruments are $y_{t-3}, \ldots, y_{t-6}, x_{it-2}, \ldots, x_{it-6}$.

Standard errors are the two step GMM standard errors. Sargan test is the standard χ^2 test for overidentifying restrictions.

1st and 2nd order serial correlations are the tests for no serial correlations first and second order correlations of the residuals.

Table 8: GMM Results specification 3

Variables	Coefficients	Std. err.	T. Stat
Number of patents $(t-1)$	-0.0169	0.0156	-1.0859
R&D $(t-1)$ (log)	0.2586	0.0184	14.0596
Training expenditures per employee $(t-1)$ (log)	0.6443	0.0275	23.4168
Market share $(t-1)$ (log)	-0.2211	0.0200	-11.0442
Size $(t-1)$	-0.0088	0.0506	-0.1741
Clerks	ref.	ref.	ref.
Unskilled workers $(t-1)$ (log)	0.0293	0.0043	6.8360
Skilled workers $(t-1)$ (log)	0.1100	0.0142	7.7670
Executive and engineers $(t-1)$ (log)	0.0601	0.0438	1.3739
Technicians and supervisor $(t-1)$ (log)	-0.1406	0.0206	-6.8136
Sargan test χ^2 (df) (p-value)	142.7416	141	0.4432
1st order serial correlation (p-value)	0.3431	0.7315	
2st order serial correlation (p-value)	-0.4320	0.6658	
Observations : 321			
Sources: Ministère de la Recherche, INPI, CEREQ			

GMM is a quasi-differenced GMM using the Chamberlain (1992) decomposition.

Instruments are $y_{t-3}, \ldots, y_{t-6}, x_{it-2}, \ldots, x_{it-6}$.

Standard errors are the two step GMM standard errors. Sargan test is the standard χ^2 test for overidentifying restrictions.

1st and 2nd order serial correlations are the tests for no serial correlations first and second order correlations of the residuals.

Appendix A Dynamic count panel data and GMM estimators

Let y_{it} denote a discrete count variable to be explained for individual i ($i = 1, ..., N$) at time t ($t = 1, ..., T$). Let x_{it} denote a vector of explanatory variables, the dynamic linear feedback model of order p is an exponential model which takes into account unobserved heterogeneity or individual fixed effects:

$$\begin{aligned} y_{it} &= \sum_{j=1}^{p} \gamma_j y_{it-j} + \exp\left(x_{it}'\beta + \eta_i\right) + u_{it} \qquad (7) \\ &= \sum_{j=1}^{p} \gamma_j y_{it-j} + \mu_{it} v_i + u_{it} \end{aligned}$$

$\mu_{it} = \exp\left(x_{it}'\beta\right)$ and $v_i = \exp\left(\eta_i\right)$ is a permanent scalar factor for the individual specific mean. In general, the unobserved fixed components η_i are correlated with the explanatory variables, $E\left[x_{it}\eta_i\right] \neq 0$. With predetermined regressors ($E\left[x_{it}u_{it-j}\right] \neq 0$, $j > 0$), the within group mean scaling estimator[13] is not consistent and Chamberlain (1992) has proposed transformations that eliminate the fixed effects from the multiplicative form and generate orthogonality conditions that can be used for consistent estimation in count data models with predetermined regressors.

For estimation by GMM, the Chamberlain (1992) quasi-differencing transformation for the LFM is given by:

$$s_{it} = \left(y_{it} - \sum_{j=1}^{p} \gamma_j y_{it-j}\right) \frac{\mu_{it-1}}{\mu_{it}} - \left(y_{it-1} - \sum_{j=1}^{p} \gamma_j y_{it-j-1}\right) \qquad (8)$$

and for predetermined x_{it}, the following moment conditions hold:

[13]The mean scaling model is: $y_{it} = \mu_{it}\frac{\overline{y_i}}{\overline{\mu_i}} + u_{it}^*$ with $u_{it}^* = u_{it} - \left(\mu_{it}/\overline{\mu_i}\right)\overline{u_i}$ and the within group mean scaling estimator minimizes the condition: $\min \sum_{i=1}^{N}\sum_{j=1}^{T} x_{it}\left(y_{it} - \mu_{it}\frac{\overline{y_i}}{\overline{\mu_i}}\right)$. See Chamberlain (1984), Blundell, Griffith and Windmeijer (2002).

$$E\left[s_{it}|y_i^{t-2},x_i^{t-1}\right]=0 \tag{9}$$

where $y_i^{t-2}=(y_{i1},y_{i2},...,y_{it-2})$ and the GMM estimator minimizes:

$$\left(\frac{1}{N}\sum_{i=1}^{N}s_i'Z_i\right)\Omega_N\left(\frac{1}{N}\sum_{i=1}^{N}Z_i's_i\right)$$

where s_i is the $(T-p-1,1)$ vector s_{it}, Z_i is the matrix of instruments and Ω_N is a weight matrix. When the full sequential set of instruments is used, the instrument matrix is given by:

$$Z_i=\begin{pmatrix} y_{i1} & x_{i1} & x_{i2} & & & & & & & \\ & & & \ddots & & & & & & \\ & & & & y_{i1} & \cdots & y_{iT-2} & x_{i1} & \cdots & x_{iT-1}\end{pmatrix}$$

If $\theta=(\gamma_1,...,\gamma_p,\beta')'$, the efficient weight matrix for the GMM estimator is:

$$\Omega_N\left(\widehat{\theta}_1\right)=\left(\frac{1}{N}\sum_{i=1}^{N}Z_i's_i\left(\widehat{\theta}_1\right)s_i\left(\widehat{\theta}_1\right)'Z_i\right)^{-1}$$

where $s_i\left(\widehat{\theta}_1\right)$ is based on an initial consistent estimate $\widehat{\theta}_1$. The one-step GMM estimator $\widehat{\theta}_1$ uses $\Omega_N=\left(\frac{1}{N}\sum_i Z_i'Z_i\right)^{-1}$. The asymptotic variance of $\widehat{\theta}_1$ is:

$$Var\left(\widehat{\theta}_1\right)=\frac{1}{N}\left(C_{\widehat{\theta}_1}'\Omega_N C_{\widehat{\theta}_1}\right)^{-1}C_{\widehat{\theta}_1}'\Omega_N\Omega_N^{-1}\left(\widehat{\theta}_1\right)\Omega_N C_{\widehat{\theta}_1}\left(C_{\widehat{\theta}_1}'\Omega_N C_{\widehat{\theta}_1}\right)^{-1}$$

where

$$C_{\widehat{\theta}_1}=\frac{1}{N}\sum_{i=1}^{N}\frac{\partial Z_i's_i\left(\theta\right)}{\partial\theta}|_{\widehat{\theta}_1}$$

The asymptotic variance of the efficient two-step GMM estimator is computed as:

$$Var\left(\widehat{\theta}_2\right)=\frac{1}{N}\left(C_{\widehat{\theta}_2}'\Omega_N\left(\widehat{\theta}_1\right)C_{\widehat{\theta}_2}\right)^{-1}$$

The Sargan test for overidentifying restrictions, based on the two-step GMM estimator, is given by:

$$N\left(\frac{1}{N}\sum_{i=1}^{N} s_i'\left(\widehat{\theta}_2\right) Z_i\right)\Omega_N\left(\widehat{\theta}_1\right)\left(\frac{1}{N}\sum_{i=1}^{N} Z_i' s_i\left(\widehat{\theta}_2\right)\right)$$

which is asymptotically chi-squared distributed with k_Z - k_θ degrees of freedom if the moment conditions are valid, where k_Z is the number of instruments and k_θ the number of parameters.