Vocational Training and Innovation

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Abstract : Human capital is considered as one of the main inputs in economic growth. Human capital can generate endogenous growth thanks to a continuous process of knowledge and externalities accumulation (Aghion and Howitt, 1998). In that context, this paper explores the relationship between innovation and vocational training. Our methodological approach allows to contribute to the literature in three manners. First, we propose different indicators of vocational training. Second, we build a count data panel with a long time data series. This deals with the issue of non-random selection and potentially with measurement error from short panels. Finally, we explicitly allow for endogeneity and fixed effects using GMM techniques. Estimations are made on a panel data set relative to French industrial firms over the period 1986-1992. Our results indicate that whatever the indicators, vocational training has 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), 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, 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. We can suppose then that a firm should increase its vocational training to increase the probability to innovate. However, very few empirical studies (Ballot et al., 2001a). 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 propose different indicators of vocational training. Second, we build a panel with a long time data series. This deals with the issue of non-random selection and potentially with measurement error from short panels. Finally, we explicitly allow for endogeneity[1] and fixed effects using GMM techniques.

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. Our sample comprises 321 firms. The originality of our database is to allow to build different training indicators and to propose 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 theory as Aghion and Howitt (1998) in the schumpeterian growth models.

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

[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.

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 come 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 (Bartel and Liechtenberg, 1987). 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 firms technological progress. 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.

Few empirical studies deal with this subject. Lynch and Black (1994) show that in the 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, by 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 other 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 different 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 as we are able to focus only on the first ones. We then 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. All the panel studies[4] confirm the stylized fact of decreasing returns to scale. Hausman, Hall and Griliches's (1984) non-dynamic estimates of the elasticity of patents with respect to R&D are in the range of $[0.3; 0.6]$ depending on the technique employed. Hall, Griliches and Hausman's (1986) estimates hover around 0.35 and are similar to those estimated in a dynamic context by Blundell, Griffith

[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.

[4] For a review concerning cross section studies, see Griliches 1990.

and Windmeijer[5] (2002) of around 0.5. Using industry level panel data Kortum and Lerner (2000) find an elasticity of $[0.48; 0.52]$.

Nevertheless, the firm level estimates, and to a lesser degree those at the industry level, may miss the spillover effects that one firm's R&D may contribute to another firm or industry's knowledge generation effort. The literature on estimating the returns to R&D, for example, finds differences of several multiples between the private returns to R&D, estimated at the firm level, and those at the national level suggesting substantial spillovers.

Some authors have extended the framework of previous studies on the patent-R&D relationship by taking into account additional determinants of patenting. These determinants can be a measure of technological spillovers (Jaffé 1986; Cincera, 1997), i.e. technological knowledge borrowed by one firm from others firms. Jaffé (1986) also finds that firms whose research is in areas where there is much research activity by other firms generate, on average, more patents per dollar of R&D and he finds the magnitudes of the spillovers to be substantial. Cincera (1997) include three additional technological determinants in the knowledge-production function. These variables are the annual flow of technological spillovers, the technological and geographical opportunities. Bresson and Abdelmoula (2005) extend the specification of Romer (1990), Bottazzi and Peri (2003), Blundell, Griffith and Van Reenen (1995) and Blundell, Griffith, Windmeijer (2002). With the linear feedback model, they are able to estimate the short and long run elasticities of innovation (e.g., patents) to R&D resources of all european sectors and regions.

In this paper, we adopt a specification along the lines of these previous authors.

[5] Studies with panel data (Hausman, Hall and Griliches 1984, 1986; Blundell, Griffith and Windmeijer 2002) along with Blundell, Griffith and Van Reenen (1995) have contributed important advances in the theory of count data estimators in a panel context. The latter two focus particularly on modeling dynamics and controlling for the unobserved heterogeneity that renders cross-sectional estimates suspect.

Following these authors a simple way to write this relationship is[6]:

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

where Q_{it} is a latent measure of the firm's technological level i at the time t, R_{it} is the R&D investment, β is the vector of unknown parameters and ν_i is the firm's patent propensity. They 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 $E\left(\varepsilon_{it} | R_{it,}R_{it-1}, \ldots, \beta, \nu_i\right) = 0$. 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 (

If, in the data, the history on R&D is limited, the linear feedback model is attractive (Blundell, Griffith and Windmeijer, 2002). In this latter, the relationship between patents and R&D is:

$$P_{it} = k(R_{it}^{\beta} + (1-\delta)R_{it-1}^{\beta} + \ldots)\nu_i + \varepsilon_{it} \tag{3}$$

In equation (

$$P_{it} = (\prod_{k=1}^{\infty}(1-\delta)^k R_{it-k}^{\beta} T_{it-k}^{\lambda})\nu_i + \varepsilon_{it} \tag{4}$$

where training investment depreciates exponentially at the same rate δ as R&D investment[7] does. So innovation of firm i depends on the elasticity β

[6]We are grateful for helpful comments from G. Bresson.

[7]We make the hypothesis that as training investment is knowledge investment, it depreci-

of patents P_{it} to R&D investments R_{it} and elasticity λ of patents to training investments. Because we have a limited history on R&D and training (7 years), we use the following linear feedback model.

$$P_{it} = (1-\delta)\, P_{it-1} + R_{it-1}^{\beta}\nu_i + T_{it-1}^{\lambda}\nu_i + \mu_{it} \tag{5}$$

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

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 (

3 Data and variables

In order to build our sample, we use three sources of informations. The first one is the French fiscal declarations 24-83 concerning the firms' vocational training annual expenditures. These data come from the CEREQ[8]. The second one is the number of patents granted by firms. These data come from the French Patent

ates as R&D investment does.

[8]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.

Office (INPI[9]). 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 firms which carry out some R&D and employ at least one full time researcher. These three databases 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[10], 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. Indeed, 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 market share is computed as the ratio of

[9]Institut National de la Propriété Intellectuelle.

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

firm's turnover to the total turnover of the sector on a two-digit-level (NAP[11] level 40). The firm size is measured by the number of employees inside the firm. These two variables are built on the model of Crépon et al. (1998). All the variables are log-linearized.

The output of innovation is measured by the number of firm patents at the date t. These data come from the INPI database. Since the firm ID SIREN codes[12] were not available in this database, it was necessary to carefully match SIREN code and firm names[13]. The patent variable is the total number of patents obtained 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 [14]. In this case, the secret can be a more effective means of protection. Furthermore, the use of patent as a measure of innovation leads to give the same weight to all innovations. Counting 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.

[11] Nomenclature des Activités et Produits.
[12] SIREN codes is the identification code of firms located in France.
[13] This work has been performed at ERMES by J.-D. Roebben, with the collaboration of INPI.
[14] According to Duguet and Kabla (1998) , only 30 % innovations are patented in France.

4 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 table

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[15]. There would be a lack of persistence of innovation. Our results are surprising. However they partly go in the sense 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 on the probability to innovate. These different results can be linked to the nature of the output measures. Thus, there would be a persistent effect in engaging in R&D activities (Peter, 2005) but not with 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 influences innovation. However, our results differ from Rogers (2004). He shows, with Australian data, that training intensity, measured as the expenditure of formal training to employees to effective full time, do not impact significantly

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

the probability to innovate. This difference can be linked to the difference in labour mobility between the two countries. Traditionally, French workers are less mobile than Australian ones, and then the risk to train employees who would quit their job, could be weaker for French employers than in Australia, as newly employees stay more in the firm.

The structure of qualifications takes part too in the explanation of the innovation. These results seem to show that innovation ensues from all the workers of the firm. However, executives and engineers have the higher impact, then the skilled workers and finally the unskilled workers. These results are similar to the ones of Pfeiffer (1997). Moreover, Ballot and Hammoudi (2002) show that skilled trained workers increase the innovation rate of the firm.

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 firms' size plays a significant part in the sources of innovation (such as R&D expenditures), the relation between the firm's size and their performances such as innovation is often no significant or negative (Mohnen and Therrien, 2002; Lööf and Heshmati, 2002; Seersucker, Duguet and Mairesse, 1998, 2000). Let us note, nevertheless, that Duguet and Greenan (1997) find a positive effect of the firm size, measured by the firm's production in volume, on the innovation. Additional regressions we carried out show that the size of firm, measured by sales, does not affect the probability to innovate.

The higher the market share is, the less the firm innovates. This result runs counter the schumpeterian assumption. Schumpeter believed that technological innovations are more likely to be initiated by large rather than small firms. This theory can be studied from two different perspectives depending on whether absolute or relative size is emphasized (Rosenberg, 1976). Relative size, measured by firm sales on industry sales is not significant either in Raymond et al. (2006).

The first model shows the role of training in innovation process. We now 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 partly 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 executives, and then the impact observed before is absorbed now by training expenditures. That would mean that it is not only to have a large share of executives that matters but to train them. Conversely, technicians and supervisors have a negative impact on innovation. Let's note first, that the coefficient of this variable seems less steady than the other ones, as in each regression it has a different impact. This result could show that innovation is done by engineers who do R&D activities or by workers who make their jobs change, through learning by doing. The intermediate workers would not deal with the innovation. We can even go further and make the assumption that technicians try to dampen the innovation process.

Thus, these three regressions show that our assumption is confirmed as training has an impact on innovation whatever the training measures we use. However, the role of competences, represented by qualification structures, is more complex. Further researches would be required on this subject.

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. More particularly, we test the impact of training on innovation, which is relatively new in the economic literature. 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 which is dedicated to these activities. Thus, high level of training seems to determine a flow of innovation and therefore a continuous rise of productivity, following previous studies on innovation and productivity (Ballot and al., 2001a). 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.

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Table 1: Summary statistic for patents

Year	Means of patents granted	Standard	Minimum error	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: Estimation results

Variables	Model I	Model II	Model III
Number of patents $(t-1)$	-0.0275 (0.0136)	-0.0036 (0.0139)	-0.0169 (0.0156)
R&D $(t-1)$ (log)	0.2164 (0.0202)	0.2296 (0.0187)	0.2586 (0.0184)
Access rate to training $(t-1)$ (log)	0.0763 (0.0111)	-	-
Number of training hours per employee $(t-1)$ (log)	-	0.0838 (0.0129)	-
Training expenditures per employee $(t-1)$ (log)	-	-	0.6443 (0.0275)
Market share $(t-1)$ (log)	-0.1170 (0.0147)	-0.1063 (0.0175)	-0.2211 (0.0200)
Size $(t-1)$ (log)	-0.0915 (0.0526)	-0.1510 (0.0573)	-0.0088 (0.0506)
Clerks	ref.	ref.	ref.
Unskilled workers $(t-1)$ (log)	0.0351 (0.0043)	0.0349 (0.0044)	0.0293 (0.0043)
Skilled workers $(t-1)$ (log)	0.1357 (0.0158)	0.1315 (0.0152)	0.1100 (0.0142)
Executive and engineers $(t-1)$ (log)	0.5572 (0.0373)	0.5116 (0.0373)	0.0601 (0.0438)
Technicians and supervisor $(t-1)$ (log)	0.0282 (0.0216)	0.0527 (0.0241)	-0.1406 (0.0206)
Sargan test χ^2 (df) (p-value)	133.3488 (0.6643)	132.2976 (0.6877)	142.7416 (0.4432)
1st order serial correlation (p-value)	0.6376 (0.5237)	0.17976 (0.8574)	0.3431 (0.7315)
2st order serial correlation (p-value)	-1.4100 (0.1586)	-1.2599 (0.2077)	-0.4320 (0.6658)
Observations : 321			
Sources: Ministère de la Recherche, INPI, CEREQ			

Standard errors are in brackets.

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. deree of freedmon: 141.

restrictions.

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

the residuals.