Vocational Training and Innovation

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Abstract : Human capital is one of the main inputs in economic growth. It generates 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 show that whatever the indicators, vocational training has a positive impact on the technological innovation.

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

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

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1 Introduction

Human capital is 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). Then human capital generates 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 by 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 benefits employees (Becker, 1962), recent studies show 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 assume then that a firm should increase its vocational training to rise the probability to innovate. However, very few empirical studies (Ballot et al., 2001a) estimate the relationship between vocational training and innovation. Their results show a positive impact of vocational training on innovation. However 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 ways. First, we use different indicators of vocational training. Second, we build a panel with a long time data series in order to control for firms' heterogeneity accounting for the unobservable and specific factors affecting the production of innovations. 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 454 firms. The originality of our database is to allow to build different training indicators and to propose dynamic analysis.

The layout of our paper is 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.

2 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 the economic growth (Benhabib and Spiegel, 1994), Nelson and Phelps (1966)

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

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

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 firms' capacities 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 with R&D activities. In the same way, from a sample of only 200 big firms, Ballot, Fakhfakh and Taymaz (1998) work out 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 the 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 on the first ones. We then test panel data.

3 The model

The relationship between innovation and R&D is traditionally interpreted as a knowledge production function (Pakes and Griliches, 1969). We adopt a specification along the lines of Pakes and Griliches (1984), Hall, Hausman and Griliches (1984,1986), Montalvo (1993), Blundell, Griffith and Windmeijer (1995), Crépon and Duguet (1993, 1997), Crépon, Duguet and Mairesse (1998, 2000). These authors consider that patents, the dependent variable, is a function of current and lagged flow of the firms' annual R&D expenditures.

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

[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.

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

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 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 neglect some sources of knowledge. For instance, 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 impact 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 (i.e., patents) to R&D resources of all european sectors and regions.

[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.

In this paper, we adopt a specification along the lines of these previous authors. A simple way to write the relationship between innovation and R&D 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.

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

where P_{it} is the number of patent and 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) assume 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:

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

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

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

In equation (4), the only regressors for patents of firm i are the current and

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

past R&D investments of firm i. Following Ballot et al. (2001a), 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 historic R&D and training investments are combined through a Cobb-Douglas technology to produce knowledge stock. Therefore equation (2) becomes:

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

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

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

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

Innovation is an inherently dynamic and nonlinear process (Blundell, Griffith and Van Reenen, 1995). Count data models, where a non-linearity is produced by the non-negative discrete nature of the data, are commonly used to analyse innovation headcounts. In theses models, 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 es-

[7] We make the hypothesis that as training investment is knowledge investment, it depreciates as R&D investment does.

timator 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) extended this estimator to dynamic models. GMM relax the strict exogeneity assumption of the regressors and allow for a feedback effect from the dependent variable to the explanatory variables by taking lagged patents as one of the regressors. Following Blundell, Griffith and Windmeijer (2002), we will estimate the equation (6) with this quasi-differenced GMM estimator[8].

The majority of compagnies make few innovations while a small group are involved in a high level of activity. This difference in unlikely to be solely attribuable to observable difference across compagnies. Unobservable permanent heterogeneity is, therefore, an important feature of any empirical model of innovation activity.

4 Data and variables

4.1 Data

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 Céreq[9]. 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

[8]For more details, see Blundell, Griffith and Windmeijer, 2002.

[9]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 center 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.

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

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.

The second database comes from the French Patent Office (INPI[11]). It gives the number of patents applied by firms. 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 last database is the French annual firm research expenditures survey. This survey is carried out by the Ministry of Research since the early 1970s and gives various information on research expenditures for firms satisfying the Frascati criteria[14]. These three databases cover the period 1986-1992.

4.2 Variables

The output of innovation is measured by the number of applied patents at the date t by the firm i during the period 1986-1992. We retain it because it is often viewed as an appropriate measure of innovation output.

However, the measure of the innovating activity by the number of patents presents some problems. Its main drawbacks 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[15]. 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 economic or

[11]Institut National de la Propriété Intellectuelle.
[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]Mainly, at least one employee working full time on research.
[15]According to Duguet and Kabla (1998) , only 30 % innovations are patented in France.

scientific weight that innovation was radical or incremental.

The number of applied patents is explained by two sources of knowledge. The first one is R&D stock. The second one is vocational training. Following the schumpeterian tradition, we include in the regression the size and the market share of the firm. The occupational decomposition is also introduced. We eventually control for the sector-based effects.

We compute research capital $k_{i,t}$ by perpetual inventory method[16]. That is, research capital for firm i at the end of year t is obtained from the formula: $k_{i,t} = (1-\delta)k_{i,t-1} + r_{i,t}$ where δ is the annual depreciation rate and $r_{i,t}$ the inflation-corrected[17] total research expenditures, excluding those purchased from outside the firm. The research capital is computed assuming an annual obsolescence rate of 15% as in Hall and Mairesse (1995), Crépon and Duguet (1997) and a presample growth rate of 5% in R&D expenditures. We start the perpetual inventory accumulation process with the earliest year of R&D data available (1986 for our sample). This variable is expressed in logarithm.

We constructed three measures of total vocational training volume: (1) the stock of training expenditure per trained employee; (2) the stock of number of training hours per trained employee; and (3) the access rate to training, in measuring the number of employees that do training on the total number of employees. As the same way as R&D capital, the stock of training expenditure and the number of training hours are worked out by the perpetual inventory method after inflation-corrected[18]. These variables are the effective measures of training. They take into account the training really achieved by firms and do not include tax payment, as a substitute to training, corresponding to the French legal obligation, unlike Ballot et al. (2001a). 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.

[16]This method for measuring R&D capital has been discussed by Griliches (1979).
[17]Base 100 in 1980.
[18]Base 100 in 1980.

The number of training hours per employee and the training expenditure per employee have been depreciated with a rate of 15%, as the R&D stock[19].

The schumpeter hypothesis claims that innovation activity increases more proportionately than the firm size (Schumpeter, 1942)[20]. The firm's size is measured by the turnover. This variable is expressed in logarithm. The market share is worked out as the ratio of firm's sales to total sales of the sector on a two-digit-level (NAF[21] 40).

Is a skilled workforce important for innovation? This question alone is worth a separate study. Depending on the nature of the technology and its rate of change, different categories of workers may be more closely related than others to a given technology (Lavoie and Therrien, 1999). Therefore, a greater proportion of professional workers in the firm would positively affect the firm's innovation performance. Therefore, we add in our model, the distribution of employees by occupational categories. This partly reflects the level of competences inside the firm. We keep 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 introduction of the distribution of employees by occupational categories is also considered as necessary when training is tested in a equation by Carriou and Jeger (1997). Indeed, otherwise, the training coefficient measures more the distribution of employees than the impact of training.

5 Results

In this section, the link between training and innovation is analyzed using the panel data sets of Céreq, INPI and the Ministry of research. We report three

[19]This rate is also used by Ballot et al. (2001a).

[20]A survey of empirical studies testing the Schumpeter hypotheses can be found in Cohen (1995).

[21]Nomenclature des Activités et Produits.

estimates from a model that explores the relationship between innovation and training, according to different measures of training. The first measure relates to training expenditure by trained employee. The second one measures the time spent training by trained employee. The last one measures the intensity of training inside the firms. To have three indicators of training gives more robustness to our results. Our results are presented in table 6 (page 26). The Sargan test always accepts the assumption 2. That proves the quality of our estimations. We present the results for the first estimate with the training stock by trained employees indicator measured by the training expenditures divided by the number of trained employees. In a second time, we compare these results with the two other estimates. The role of training on innovation is confirmed.

Results show 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 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.

Results show also 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. However, the coefficient of this variable is rather weak in comparison with the one found in the literature. If we compare with the result of Blundell et al. (2002), the difference of the R&D coefficient value can be partly explained first by the introduction of a new source of knowledge through the variable of training[22]. Second this result can be linked to the composition of the sample as their one contains only large firms and the average number of patents is much more important (35,25 vs. 4,63). American big firms could have a specific strategy to patent.

Conversely, the number of patents obtained into $(t-1)$ decreases the probability to innovate in period $t-2$, $t-3$, ... Our results differ from the studies on the persistence of innovation. Studies, measuring innovation by patent, find mainly no persistence effect. We can assume that patenting is not an annual activity. Firms that patent in year t, seldom patent in year $(t+1)$ as patenting is costly and requires specific characteristics of the new knowledge. This result is confirmed by the fact that in our model, lagged patents in $(t-2)$ or more are not significant. There would be a negative impact of patent applied in $(t-1)$ and no persistence for previous patents which is more consistent with previous studies on patented innovation. This result can also be linked to the fact that the patent variable of our sample contains 73% of zero. Finally, the result can be in line with the destructive creation hypothesis. As long as the firm is not threatened, it does not innovate. Our results contrast also with those of studies when innovation is measures by R&D or innovation. Duguet and Mongon (2002) find evidence of strong persistence of innovation in all French manufacturing industries. However, these authors measure the persistence by the fact to innovate two or four years before on the probability to innovate. We can assume that firms innovate more than they patent and the lag is more important than just than one year. Raymond et al. (2007) show that once the individual effects and the endogenous initial conditions are allowed for, there is persistence of innovation, measured with lagged probability to innovate variable on the probability to innovate, only when firms belong to high-tech sector. These different results can be linked to the nature of the output measures. Thus, there would be a

[22]We estimate the model only with R&D variables, that means without other sources of knowledge (training or even occupational structure). The R&D coefficient is much higher. This result confirms the importance of taking into account several source of knowledge. The estimate is available on request

persistent effect in engaging in R&D activities (Peter, 2005) and in innovating but not in patenting.

The structure of qualifications takes part too in the explanation of innovation. These results seem to show that the non-executive employees have a weaker probability to innovate than executives and engineers. 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. This result could be linked to the nature of the output which is patent and not innovation. We can suppose that patent activities are more realized by executives and researchers.

The firm's size, measured by the logarithm of turnover, has a significant impact. This result invalidates 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. Our result could be linked to the structure of our sample, which is biased with an over-representation of big firms.

The higher the market share is, the more the firm innovates. This result confirms the schumpeterian assumption. Schumpeter believed that technological innovations are more likely to be initiated by large rather than small firms.

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. The results are very similar. The main difference lies on the value of the training coefficient. The coefficient of training expenditure is much more higher than the ones of training time and of access rate to training. That would show that training is important but the level of expenditures dedicated to training is more crucial for innovation.

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.

6 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 highlight 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).

However our model meets some limits linked to the choice of the model. We use count panel data but further researches would be necessary with a zero inflated poisson in order to take into account the decision to patent. Moreover, 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. Finally, it would worthwhile to test the inverse relation that means the impact of innovation on vocational training.

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Table 1: Summary statistic for patents

Year	Means	Std. err.	Min.	Q_1	Med.	Q_3	Max.
All years	4.63	18.04	0	0	0	2	234
1986	3.72	14.24	0	0	0	1	190
1987	3.97	15.09	0	0	0	1	208
1988	4.56	17.52	0	0	0	1	177
1989	4.84	19.62	0	0	0	2	234
1990	4.96	19.53	0	0	0	2	210
1991	5.17	19.56	0	0	0	2	198
1992	5.18	19.94	0	0	0	2	193
Observations: 454							
Sources: Ministère de la Recherche, INPI, Céreq							

Table 2: Summary statistic for training expenditures stock per employee

Year	Means	Std. err.	Min.	Q_1	Med.	Q_3	Max.
All years	19 529.90	17 270.97	1 827.62	8 397.71	13 920.63	24 731.18	179 135.43
1986	14 811.25	13 904.20	1 827.62	6 763.33	10 004.64	18 359.77	153 721.54
1987	16 121.42	14 530.52	3 604.87	7 329.16	10 944.75	20 201.22	155 340.88
1988	17 517.69	15 445.12	2 789.04	7 746.30	12 212.90	22 159.84	153 991.47
1989	18 946.20	16 492.20	2 547.12	8 446.87	13 391.05	23 735.91	157 257.44
1990	21 002.32	17 866.09	3 313.78	9 304.56	15 012.33	27 148.03	156 368.44
1991	23 065.49	19 348.27	4 632.64	10 364.18	16 511.66	29 210.48	179 135.42
1992	25 244.91	19 940.01	4 023.34	12 076.21	18 854.76	32 552.75	178 411.52
Observations: 454							
Sources: Ministère de la Recherche, INPI, Céreq							

Table 3: Summary statistic for access rate to training

Year	Means	Std. err.	Min.	Q_1	Med.	Q_3	Max.
All years	33.42	22.41	0	15.82	30.64	46.57	187.00
1986	25.21	18.12	0	12.70	22.59	36.11	128.10
1987	29.01	20.91	0	13.33	24.88	40.92	120.49
1988	31.10	21.44	0	14.45	28.20	44.47	114.68
1989	34.25	21.49	0	17.97	31.78	46.94	116.07
1990	37.23	23.70	0	19.16	35.71	51.76	187.00
1991	38.38	23.87	0	19.04	37.57	53.24	137.62
1992	38.76	23.29	0	20.43	38.36	54.97	161.46
Observations: 454							
Sources: Ministère de la Recherche, INPI, Céreq							

Table 4: Summary statistic for stock of training hours

Year	Means	Std. err.	Min.	Q_1	Med.	Q_3	Max.
All years	77.35	69.07	0	29.13	57.95	105.66	645.34
1986	58.19	52.34	0	21.34	44.70	78.41	472.84
1987	63.75	55.68	0	24.16	50.02	86.35	474.35
1988	70.24	64.53	0	27.19	53.38	94.59	520.77
1989	75.85	67.86	0	28.55	57.13	104.54	575.28
1990	83.57	74.06	0	31.55	64.79	114.74	645.34
1991	91.22	77.54	0	36.43	69.85	124.25	558.98
1992	98.62	77.85	0	40.62	80.61	137.36	530.02
Observations: 454							
Sources: Ministère de la Recherche, INPI, Céreq							

Table 5: Summary statistic for explanatory variables

Variable	Means	Std. err.	Min.	Q_1	Med.	Q_3	Max.
R&D Stocks	102.06	231.34	0	0	18.27	104.68	3.30E3
Size	2.72E6	10.88E6	9.68E3	111.40E3	382.09E3	1.33E6	177.46E3
Market share	0.01	0.04	3.84E-5	8.84E-4	3.23E-3	0.01	0.66
Clerks	0.14	0.10	0	0.08	0.12	0.17	1.00
Technicians and supervisor	0.18	0.11	0	0.10	0.15	0.23	0.70
Unskilled workers	0.19	0.21	0	2.05E-3	0.09	0.33	1.00
Skilled workers	0.36	0.19	0	0.21	0.35	0.51	0.96
Executive and engineers	0.12	0.08	0	0.06	0.09	0.14	0.68

Observations: 454

Sources: Ministère de la Recherche, INPI, Céreq

Table 6: Estimation results

	Model I		Model II		Model III		Model IV	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
Number of patents $(t-1)$	-0.4504	0.0124	-0.4539	0.0115	-0.4536	0.0113	-0.4539	0.0114
R&D stock $(t-1)$ (log)	0.0696	0.0159	0.0560	0.0160	0.0511	0.0168	0.0666	0.0147
Stock of training hours per employee $(t-1)$ (log)	-	-	-	-	0.0302	0.0154	-	-
Access rate to training $(t-1)$	-	-	-	-	-	-	0.1089	0.0199
Training stock per employee $(t-1)$ (log)	-	-	0.1640	0.0198	-	-	-	-
Market share (log)	1.6819	0.8508	1.7331	0.7428	2.0827	0.8409	2.1267	0.8216
Size (log)	0.4225	0.0318	0.3881	0.0313	0.4129	0.0291	0.3752	0.0314
Number of competitors	0.0296	0.0328	0.0955	0.0314	0.0301	0.0320	0.0478	0.0297
Clerks	-1.3262	0.3435	-1.3673	0.2976	-1.5408	0.3074	-1.4345	0.2863
Technicians and supervisor	-1.2958	0.3373	-1.3013	0.2890	-1.5039	0.2963	-1.3878	0.2787
Skilled workers	-1.4870	0.3228	-1.3800	0.2828	-1.6248	0.2959	-1.4953	0.2695
Unskilled workers	-0.8177	0.3376	-0.7318	0.2796	-0.9967	0.3084	-0.9087	0.2700
Intermediate goods industry	0.2556	0.3740	0.2044	0.3655	0.2008	0.3911	0.1832	0.3728
Capital goods industry	0.5779	0.3586	0.5237	0.3597	0.5467	0.3778	0.5008	0.3605
Food goods industry	0.1018	0.3924	0.0373	0.3859	0.0570	0.4032	0.0525	0.3885
Sargan test χ^2 (p-value)	181.35	0.52	204.70	0.33	198.76	0.45	203.33	0.36
Degree of Freedom	183		197		197		197	
1st order serial correlation (p-value)	1.18	0.23	1.34	0.17	1.26	0.20	1.33	0.18
2st order serial correlation (p-value)	-2.44	0.01	-2.50	0.01	-2.51	0.01	-2.21	0.02
Observations : 454								
Sources: Ministère de la Recherche, INPI, Céreq								

Standard errors are in brackets.

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

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.