Firms' human capital, R&D and innovation: a study on French firms

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Abstract

Human capital is one of the main engine for economic growth. It generates endogenous growth thanks to a continuous process of accumulation of knowledge and externalities (Aghion and Howitt, 1998). This paper explores the relationship between innovation and firm provided training. Our methodological approach contributes to the literature in three ways. We propose various indicators of firm provided training. We build a count data panel with a long time data series to deal with the issue firms' heterogeneity. We propose a dynamic analysis. Estimations are made on a panel data set for French industrial firms over the period 1986-1992. Our results show that, on the job training has a positive impact on technological innovation whatever the indicators.

Keywords: Patents, R&D, on the job training, count panel data, linear feedback model

JEL Code: 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 and other attributes embodied in individuals that are relevant to economic activity. Human capital generates endogenous growth through a continuous process of accumulation of knowledge and externalities (Aghion and Howitt, 1998). Although generally considered in theoretical models as the product of school education, human capital accumulation is actually a more complex process. First, school is neither an exclusive nor a sufficient method of training people (Legros, 2005; Mincer, 1993). It is a first step, which is supplemented by informal learning processes related to experience and by formal learning processes such as on the job training. While human capital theory considers that firms have no interest in investing in on the job training as it benefits employees only (Becker, 1962), recent studies show that training benefits firms through direct payments or lower wages (Bishop, 1996; Booth and Snower, 1996; Booth and Bryan, 2002). Empirical studies show that human capital, including that fraction of it acquired through training, has a positive impact on labor productivity and increases firms'profits (Bartel, 1989, 1994, 2004; Carriou and Jeger, 1997). Firms expect training to bring them efficiency gains and better adaptation to technical change.On the job training becomes an investment in the same way as R&D. It can be assumed that a firm should increase its continuous training to raise the probability of innovating. Results of the very few empirical studies on the subject (Ballot, Fakhfakh, and Taymaz, 2001) show a positive impact of on the job training on innovation. However more studies are required to confirm these results.

This paper investigates the impact of on the job training on innovation's production in France [1]. Our methodological approach contributes to the literature in three ways. First, we use various indicators of on the job training. Second, we build a panel with a long time data series to control for firms' heterogeneity accounting for the unobservable and specific factors affecting the production of innovations. We also propose a dynamic analysis.

Our data are from French tax returns for firms' annual expenditure on on the job training, the INPI[2] database on patents, the SESSI annual survey of firms and the R&D survey issued by the French Ministry of Research. The four databases cover the period from 1986 to 1992. Our sample consists on a pseudo panel 4430 observations.

The article is organized as follows. In the next section, we analyse the literature on the connection between on the job training and innovation. The model and the econometric specification are examined in section 3. The data are presented and variables defined in section 4. The main results are discussed in section 5. The section 6 concludes.

[1] On the job training is focalised in this article on the one financed by firms for their own employees. It can take different forms such as training for the adaptation to a new workstation, to the evolution of the job or to the development of new competencies. We can already note that since 1971, the French firms have a legal obligation to finance on the job training.

[2] Institut National de la Propriété industrielle/French patent and trademark office.

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. The development and diffusion of knowledge are crucial sources of growth, while human capital investment is the most important input for the advancement of science and knowledge. This idea developed by Nelson and Phelps (1966) has been taken up by proponents of endogenous growth theory such as Aghion and Howitt (1998) in Schumpeterian growth models.

Against the standard concept of human capital, which considers that human capital is only another factor to take into account in measuring economic growth Nelson and Phelps (1966) and Benhabib and Spiegel (1994), produce evidence that education increases the capacity to innovate (creation of activities, products, and technologies) and fosters the adoption of new technologies. They consider that "*education enhances the ability to receive, decode, and understand information*", (see Nelson and Phelps, 1966, pg. 69). The interesting and innovative results of this approach stem from the close link it establishes between technical progress and education. One of the first conclusions of Benhabib and Spiegel (1994) and Nelson and Phelps (1966) is that the growth rates of productivity and innovation are positively correlated with the level of education, in particular with the number of persons with high school or university diplomas.

In the line of these results about the importance of education, some studies show the importance of absorptive capacity as a key factor behind firms' technological progress (Cohen and Levinthal, 1990a). Absorptive capacity appears to be one of the most important determinants of the firm's ability to acquire, assimilate and profitably utilize new knowledge to increase its innovation performance. Firms need to raise their absorptive capacities to acquire, transform and exploit knowledge which can lead to innovations (Cokburn and Henderson, 1998; Daghfous, 2004). Therefore, when firms have greater absorptive capacity, it would increase their performance of innovation innovation activities (Cohen and Levinthal, 1990a). Cohen and Levinthal (1990a) claim the learning capacity of firms depends on their internal capacities, which can be measured by the number of researchers in the R&D department. However authors have emphasized internal R&D as the key component of the absorptive capacity of external R&D spillovers. We will point here to the role of human resources management, and more precisely the human capital stock in the firm measured by continuous training. Our hypothesis is that on the job training increase the firm's capacity to innovate.

Few empirical studies deal with this subject. Lynch and Black (1995) show that in the United States, the ratio of educated employees is positively correlated with R&D activities. Baldwin and Johnson (1996), Baldwin and Yates (1999), Baldwin (2000), Laplagne and Bensted (2002) confirm the close connection between on the job training and innovation. They identify various types of innovative firms and show that when innovators are divided into quartiles on the basis of their innovativeness, some 80% of firms in the top of quartile are found to have a on the job training program. Similarly, from a sample of only 200 big firms, Ballot, Fakhfakh, and Taymaz (1998) calculate a training stock of the firm, by cumulating on the job training expenditure from 1987 to 1993. They test a production function in which they include possible interactions between human capital and R&D and conclude that continuous training and R&D are significant factors of the production function. The main limits of this model are the small size of the sample and the absence of longitudinal data with which to control for the unobserved and specific characteristics of firms.

More recently, Ballot, Fakhfakh, and Taymaz (2001) find a positive effect of intern on the job training on the probability of innovating for French firms. They explain this probability among other variables by an R&D indicator and a human capital variable measured by a depreciated stock of in-service training expenditure. These various models propose interesting results but need to be completed. To that end, using pseudo panel data, we estimate a knowledge production function in which we introduce on the job training.

3 The model and estimation method

3.1 Model set-up

The relationship between innovation and R&D is traditionally interpreted as a knowledge production function (Griliches, 1990; Pakes and Griliches, 1984). A simple way to write the relationship between innovation and R&D is:

$$Q_{it} = g\left(R\&D_{it}, v_i\right) \tag{1}$$

where Q_{it} is a latent measure of the firm's technological level i at the time t, $R\&D_{it}$ is the R&D expenditure and v_i is the unobservable individual effect. As mentioned in the previous section, we assume that there exist important complementarities between R&D and on the job training and so we introduce them together in the knowledge production function. Therefore equation (1) becomes:

$$Q_{it} = g\left(R\&D_{it}, T_{it}, v_i\right) \tag{2}$$

where $R\&D_{it}$ and T_{it} are respectively R&D investment and on the job training expenditure at date t.

Our indicator firms' innovation is the number of patents applied during one year. Because the relationship between patent and knowledge is stochastic (Griliches, 1990; Levin, Klevorick, Nelson, and Winter, 1987), it can be written as:

$$p_{it} = Q_{it} + \varepsilon_{it} \tag{3}$$

where p_{it} is the dependent variable which describes the number of patents applied by firm i at time t, ε_{it} is an unobserved error and $E\left(\varepsilon_{it} | R\&D_{it}, T_{it}, v_i\right) = 0$.

The number of patents is restricted to non-negative integer values. Count panel data methods are particularly useful for investigation of the relationship between the patenting process and R&D (Gouriéroux, Monfort, and Trognon, 1984a; Winkelmann, 2000). Therefore p_{it} is assumed to be Poisson distributed with mathematical expectation $\lambda_{it} > 0$. The link between patents, $R\&D_{it}$, on the job training, T_{it} and a set of control, X_{it}, including firm characteristics and sectoral effects, is assumed to be an exponential function form:

$$\lambda_{it} = E\left(p_{it} | R\&D_{it}, T_{it}, X'_{it}, \nu_i\right) = \exp\left[\beta_0 + \beta_1 \log\left(R\&D_{it}\right) + \beta_2 \log\left(T_{it}\right) + X'_{it}\theta + \nu_i\right] \tag{4}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$ and where θ is a $(K \times 1)$ vector of unknown parameters.

It is possible to embed lagged dependent variables in this model (Blundell, Griffith, and Windmeijer, 2002; Crépon and Duguet, 1997). We follow Blundell, Griffith, and Windmeijer (2002). The dynamic specification considered here is a linear feedback model (LFM). The mean function for dynamic model includes lagged dependent variable, which enters linearly, other conditioning variables in the exponential function, and the individual effects. For the case of one lag of the dependent variable, the conditional mean function for LFM is:

$$\lambda_{it} = \gamma p_{it-1} + \exp\left[\beta_0 + \beta_1 \log\left(R\&D_{it}\right) + \beta_2 \log\left(T_{it}\right) + X'_{it}\theta + \nu_i\right] \tag{5}$$

where p_{it-1} is the patent applied at date $(t-1)$.

3.2 Estimation method

It is clear by examination of equation (5) that the strict exogeneity assumption of the Hausman, Hall, and Griliches (1984) conditional Poisson estimation method is not satisfied for this specification. An alternative non-linear quasi-differenced GMM estimator is proposed by Chamberlain (1992). This estimator relaxes the assumption of strict exogenity and instead assumes that the regressors are predetermined[3]. But as noted in Blundell, Griffith, and Windmeijer (2002), if this estimator is consistent, it has a problem of weak instrument bias when the serie is highly persistent.

An alternative to measuring the unobserved heterogeneity is to use pre-sample information. Blundell, Griffith, and Van Reenen (1995) argue that "*the main source of unobserved heterogeneity*" in innovation activities "*lies in different knowledge stocks*" (see Blundell, Griffith, and Van Reenen, 1995, pg. 338). So "*the permanent capacities of companies successfully to commercialise new products and processes should*

[3] A regressor is predetermined when it is not correlated with current and future shocks, but it is correlated with past shocks (Blundell, Griffith, and Windmeijer, 2002). For applications of this estimator, see Montalvo (1993), Montalvo (1997), Blundell, Griffith, and Van Reenen (1995), Blundell, Griffith, and Windmeijer (2002), Cincera (1997), Crépon and Duguet (1997).

be reflected in the pre-sample history of innovative success" (see Blundell, Griffith, and Van Reenen, 1995, pg. 338). Monte Carlo experiments (Blundell, Griffith, and Windmeijer, 2002) show that the pre-sample mean (PSM) estimator outperforms other estimators, particularly when the number of observations is small. Specifically, the level estimator generates upwardly biased estimates, and in contrast, the estimates by the within-group estimator are biased downwards. The quasi-difference GMM estimator also generates downwardly biased estimates when the number of observations is small. As a result, the PSM estimator outperforms these estimators in almost all settings in the experiments. Following Blundell, Griffith, and Van Reenen (1995) we use the pre-sample mean estimator to estimate our dynamic count data model.

The pre-sample mean estimator takes the following form:

$$p_{it} = \gamma p_{it-1} + \exp\left[\beta_0 + \beta_1 \log\left(R\&D_{it}\right) + \beta_2 \log\left(T_{it}\right) + X_{it}'\theta + \rho \log \overline{p}_{ip} + v_i\right] \tag{6}$$

where $\overline{p}_{ip}$ is the pre-sample information of p, and $\overline{p}_{ip} = \frac{1}{S+1}\sum_{s=0}^{-S} p_{is}$, where S is the number of pre-sample observations and $s = 0, -1, -2, \ldots, -S$.

In order to calculate the pre-sample mean estimator, the following moment conditions are solved (Blundell, Griffith, and Windmeijer, 2002):

$$\sum_{i=1}^{N}\sum_{t=2}^{T} z_{it}\left(p_{it} - \gamma p_{it-1} - \exp\left[\beta_0 + \beta_1 \log\left(R\&D_{it}\right) + \beta_2 \log\left(T_{it}\right) + X_{it}'\theta + \rho \log \overline{p}_{ip} + v_i\right]\right) = 0 \tag{7}$$

where :

$$z_{it} = \left(1, p_{it-1}, \log\left(R\&D_{it}\right), \log\left(T_{it}\right), X_{it}', \log \overline{p}_{ip}\right) \tag{8}$$

4 Data and variables

4.1 Data

In order to build our sample, we use four databases. The first is the French 24-83 tax returns for firms' annual on the job training expenditure. These data are from the Céreq (Centre d'études et de recherches sur les qualifications)[4]. With records dating from the introduction of the 1971 statute, firms' annual tax returns (n°. 24-83) are the oldest and most consistent source of statistics on on the job training in France. This source provides various indicators on firms' training expenditure[5], physical volumes of training, and its main characteristics: duration, average unit cost. Our sample is derived from a sub-sample. For the "Provence Alpes Côte d'Azur" region, the Céreq

[4]For more information concerning Céreq, see the web site http://www.cereq.fr.

[5]Since 1993 the official minimal rate has been 1,5% of the payroll for firms with 10 employees or more.

took 10% of firms with 10-19 employees, 20% of the firms with 20-49 employees and 50% of the firms with 50-500 employees. For other regions, sampling is exhaustive.

The second database is from the French Patent Office (INPI). It indicates the number of patent applications by firms. Since firms' ID SIREN codes[6] were unavailable in this database, SIREN codes had to be carefully matched with firms' names.[7]

The third database, the SESSI Annual Survey of Firms (EAE) yields information about the characteristics of firms such as size, sector and turnover. The final database is the French annual survey of firms' research expenditure. This survey has been carried out by the Ministry of Research since the early 1970s and gives various information on research spending for firms satisfying the Frascati criteria[8]. These four databases cover the period 1986-1992. Our sample comprises 993 French firms.

4.2 Variables

The output of innovation is measured by the number of patent applications at date t by firm i during the period 1986-1992[9]. This is used because it is often viewed as an appropriate measure of innovation output. However, measuring innovative activity by the number of patents raises problems. Its main drawbacks are well-known (Griliches, 1990; Levin, Klevorick, Nelson, and Winter, 1987). First, the number of patents held by a firm does not reflect the exact number of innovations carried out by that firm. Not every innovation is 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, secrecy may be a more effective means of protection. Furthermore, the use of patents as a measure of innovation means the same weight is attributed to every innovation. Counting patents relies on the implicit assumption that each patent has the same economic or scientific weight, that innovation is radical or incremental.

The number of patent applications is explained by two sources of knowledge: R&D stock and on the job training. In the Schumpeterian tradition, we include the firm's size and market share in the regression. An analysis by occupation is also introduced. We explain the probability to innovate by the R&D expenditure per employee. This variable is expressed in logarithm.

We constructed three measures of on the job training: (1) the on the job training expenditure per employee trained; (2) the number of continuous training hours per employee trained; and (3) the access rate to continuous training, by measuring the number of employees that undergo training out of the total number of employees. They take into account the training actually undertaken by firms for their employees. If we obtain similar results with all three variables, then training really does have

[6]SIREN codes are the identification codes of firms located in France.

[7]We are grateful to J.-D. Roebben for providing us the data.

[8]Mainly, at least one employee working full time on research.

[9]There is more recent data but these one are not in our disponibility.

[10]Duguet and Kabla (1998) claim only 30% of innovations in France are patented.

an impact on innovation. A vector of additional explanatory variables including the firm's market share, firm size and occupational categories is introduced. Schumpeter's hypothesis claims that innovative activity increases more proportionately than the firm size (Schumpeter, 1942).[11] Firm size is measured by total revenues. Market share corresponds to the ratio of firm's sales to total sales of the sector on a two-digit-level (NAF[12] 40). The following variables: R&D expenditure, on the job training hours per employee, on the job training expenditure per employee, market share, firm size and number of competitors are expressed in logarithm.

Is a skilled workforce important for innovation? This question alone would be 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 highly qualified workers in the firm would positively affect the firm's innovation performance. Therefore, we include the distribution of employees by occupational categories in our model. This partly reflects the level of skills within the firm. We keep five main categories: engineers and executives, skilled workers, unskilled workers, clerks, technicians and supervisors. Each is introduced in the model as the share of workers of one category out of the total number of employees in the firm (average over the year). Introducing the distribution of employees by occupational categories is also considered necessary when training is tested in an equation, by Carriou and Jeger (1997). Otherwise, the training coefficient measures more the distribution of employees than the impact of training.

As described in subsection (3.2), we introduce in the regression a pre-sample information. The pre-sample mean of patent uses the years 1973-1984.

5 Results

In this section, the link between training and innovation is analyzed using the unbalanced panel data set from the Céreq, INPI and Ministry of Research. It contains 4430 observations.[13] In table (6), we present the results of estimating equation (3.2) using three measures of training. We estimate three models. The only difference between these models is the measure of training. In all three models, training has a positive and statistically significant effect on innovation. The coefficients of the three variables are quite close. The difference could be explained by some measurement errors. Our results confirm our hypothesis that on the job training and innovation are correleted. More precisely, continuous training have a positive impact on inovation. However, our results differ from Rogers (2004) who shows, with Australian data, that training intensity, measured as the expenditure on formal training of employees to effective full

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

[12] In French: Nomenclature des Activités et Produits.

[13] Summary statistics using the balanced panel data set are in appendice. Statistics with the unbalanced panel data set are available on request.

time, does not significantly impact the probability of innovating. This difference may be related to the difference in labour mobility between the two countries. Traditionally, French workers are less mobile than their Australian counterparts, and they stay longer in a firm. So the risk of training employees who subsequently quit their jobs may well be lower for French employers than for Australia employers, as new employees stay with firms longer.

The results also show that past R&D expenditure has a significant and positive impact on innovation. Moreover, its impact remains stable for all the different estimates. These results confirm the numerous models of knowledge production (Crépon and Duguet, 1993, 1997; Crépon, Duguet, and Kabla, 1996; Griliches, 1990). The more a firm invests in R&D, the more patents it applies. However, the coefficient of this variable is rather weak in comparison with that found in the literature. From our results, a 10% increase in R&D intensity will have an impact of 0.5% on the firm's total number of patents. If we compare this with the result of Blundell, Griffith, and Windmeijer (2002), the difference of the R&D coefficient value can be partly explained first by the introduction of a new source of knowledge such as training.[14] Second this result can be linked to sample composition as theirs contains only large firms and the average number of patents is much greater (35.25 vs. 4.63). Big US firms may have a specific strategy on patenting. Indeed, it seems that French firms patented less much that the American ones in the 70's and 80's (Englander, Evenson, and Hanazaki, 1988). We could then expect a smaller impact of R&D expenditure on innovation at a similar level of expenditure. Moreover, we introduce a stock of knowledge, through the method of the pre-sample means. This coefficient is very high. This result shows the importance of internal capacities and can also explain the lower coefficient of R&D in our model.

Conversely, the number of patents obtained at $(t-1)$ reduces the probability of innovating in period t. Our results differ from studies on the persistence of innovation. Studies, measuring innovation by patent, generally report 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 at $(t-2)$ or more are not significant. There seems to be a negative impact of patent applications at $(t-1)$ and no persistence for previous patents. This result is more consistent with previous studies on patented innovation. It can also be linked to the fact that the patent variable of our sample contains many firms that have no innovations. According to our experience coefficients are weaker when we do not control for the decision to innovate. Finally, the result may 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 where innovation is measured by R&D or innovation. Duguet and Monjon (2002) find evidence of strong persistence of innovation in

[14] We estimate the model with R&D variables only, i.e. 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 sources of knowledge. The estimate is available on request.

all French manufacturing industries. However, these authors measure persistence by the impact of having innovated two or four years earlier on the probability of innovating now. We can assume that firms innovate more than they patent and the lag is greater than just one year. Raymond, Mohnen, Palm, and Van der Loef (2007) show that once the individual effects and the endogenous initial conditions are allowed for, there is persistence of innovation, measured by the lagged probability of the innovating variable on the probability of innovating, only when firms belong to the high-tech sector. These different results may be related to the nature of the output measures. Thus, there seems to be a persistent effect in engaging in R&D activities (Peters, 2005) and in innovating but not in patenting.

The structure of qualifications also accounts for innovation in part. These results seem to show that non-executive employees have a lower probability of innovating than executives and engineers. These results are similar to those of Pfeiffer (1997). This result could be linked to the nature of the output, which is patents and not innovation. Presumably patent activities are carried out more commonly by executives and researchers.

Firm size, measured by the logarithm of total revenues, has a significant impact.[15] This result invalidates the recent studies showing that even if firm size plays a significant part in the sources of innovation (such as R&D expenditure), the relation between firm size and performance, such as innovation, is often not significant or negative (Crépon, Duguet, and Mairesse, 1998, 2000; Lööf and Heshmati, 2002; Mohnen and Therrien, 2002). Let us note, nevertheless, that Duguet and Greenan (1997) find a positive effect of firm size, measured by the firm's production in volume, on innovation.

Concentration measured by the number of competitor in a sector has a positive impact on the probability of innovation. This resulty is in line with Scherer (1965a) and Scherer (1965b). This result confirms the importance of competition to innovate. However, the impact of market share is different. Indeed, its coefficient is only significant with training expenditure. It is negative. Then, the greater its market share, the less a firm innovates. This result differs from the Schumpeterian assumption that technological innovations are more likely to be initiated by firms with great market power.[16]The simultaneous introduction of these two variables enables us to precise the importance of the market structure on the innovation.

These three regressions confirm our assumption because on the job training has an impact on innovation whichever measure we use. However, the role of skills, represented by qualification structures, is more complex. Further research is required on this subject.

[15]We also estimate the model with a size variable, measured by the logarithm of the number of employees. The results are unchanged.

[16]We control the model with sector effects by introducing three sector variables. The sector variables are not significant and the results remain unchanged.

6 Conclusion

Recently the focus of empirical research on innovation has shifted from innovation input to innovation output. In this paper we empirically analyze the connection between the input to the innovation process and the output from French manufacturing firms. More particularly, we test the impact of on the job training on innovation, which is a relatively new topic in the economic literature. The following conclusions can be drawn. The estimations with different measures of continuous training confirm his impact on the innovation process. High levels of continuous training seem to generate a flow of innovation and therefore a continuous rise in productivity, which is consistent with previous studies on innovation and productivity (Ballot, Fakhfakh, and Taymaz, 2001).

This paper has also focused on the importance in modeling of unobserved heterogeneity with dynamic feedback mechanisms. Economic theory suggests that innovation activity is an inherently dynamic and nonlinear process among heterogeneous firms. Standard ways of dealing with these problems generally rely on the assumption of strict exogeneity but this is clearly inappropriate for the innovation process. To deal with certain econometric problems arising from the panel data structure and from the discrete nature of the dependent variable, alternative econometric models for count panel data were investigated.

However our model comes up against certain limitations related to the choice of model. We use count panel data but further research would be necessary with a zero inflated Poisson model to take account of decisions to patent. Further work might study the impact of training by occupational categories to test our hypothesis that executives benefit more from training than other categories. Finally, it would be worthwhile exploring the inverse relation; that of the impact of innovation on the job training.

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References

ABDELMOULA, M., AND G. BRESSON (2005): "Patents and R&D spillovers in some European regions: a dynamic count panel," Working Paper, ERMES (CNRS), Université Paris II.

AGHION, P., C. HARRIS, P. HOWITT, AND J. VICKERS (2001): "Competition, Imitation and Growth with Step-by-Step Innovation," *Review of Economic Studies*, 68, 467–492.

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

AL-OSH, M., AND A. ALZAID (1987): "First-order integer valued autoregressive (INAR(1)) process," *Journal of Time Series Analysis*, 8, 261–275.

ALZAID, A., AND M. AL-OSH (1990): "Integer-valued *p*th order autoregressive structure (INAR(p)) process," *Journal of Applied probability*, 27, 314–324.

ARROW, K. J. (1973): "Higher Education as a Filter," *Journal of Public Economics*, 2, 193–216.

BALDWIN, J., AND J. JOHNSON (1996): *The Implications of Knowledge-Based Growth for Micro-Economic Policies*chap. Human Capital Development and Innovation: A Sectoral Analysis. University of Calgary Press.

BALDWIN, J. R. (2000): "Innovation and Training in New Firms," Analytical Studies Branch Research Paper Series 2000123e, Statistics Canada, Analytical Studies Branch.

BALDWIN, J. R., AND J. YATES (1999): "Innovation, Training and Success," Analytical Studies Branch Research Paper Series 1999137e, Statistics Canada, Analytical Studies Branch.

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

——— (2001): "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.

BARTEL, A. P. (1989): "Formal Employee Training Programs and Their Impact on Labor Productivity: Evidence from a Human Resources Survey," Discussion Paper 3026, National Bureau of Economic Research.

——— (1994): "Productivity Gains from the Implementation of Employee Training Programs," *Industrial Relations*, 33(4), 411–25.

——— (2004): "Human resource management and organizational performance: Evidence from retail banking," *Industrial and Labor Relations Review*, 57(2), 181–203.

BARTEL, A. P., AND F. R. LICHTENBERG (1987): "The Comparative Advantage of Educated Workers in Implementing New Technology," *Review of Economics and Statistics*, 69(1), 1–11.

BECKER, G. (1962): "Investment in Human Capital: A Theorical Analysis," *Journal of Political Economy*, (70), 1–49.

BECKER, G. (1975): *Human Capital*. Columbia University Press, New-York, 2nd edn.

BENHABIB, J., AND M. M. SPIEGEL (1994): "The Role of Human Capital in Economic Developement. Evidence from Aggregate Cross-country Data," *Journal of Monetary Economics*, (70), 143–173.

BISHOP, J. H. (1996): "What we know about employer-provided training: a review of the literature," , cornell university, center for advanced human resources studies, *Working Paper*, n°. 96-09.

BLUNDELL, R., AND S. BOND (1998): "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87, 115–149.

BLUNDELL, R., R. GRIFFITH, AND J. VAN REENEN (1995): "Dynamic count data models of technological innovation," *The Economic Journal*, 105(429), 333–344.

BLUNDELL, R., R. GRIFFITH, AND F. WINDMEIJER (2002): "Individual effects and dynamics in count data models," *Journal of Econometrics*, 108(1), 113–131.

BOOTH, A., AND D. SNOWER (1996): *Acquiring Skills, Market Failures, Their Symptoms and Policy Responses*. Cambridge University Press.

BOOTH, A. L., AND M. L. BRYAN (2002): "Who Pays for General Training? Testing Some Predictions of Human Capital Theory," EALE, Paris, 43 pages.

BOTTAZI, L., AND G. PERI (2003): “Innovation and spillovers in regions: evidence from European patent data,” *European Economic Review*, 47(4), 687–710.

CARRIOU, Y., AND F. JEGER (1997): “La formation continue dans les entreprises et son retour sur investissement,” *Economie et Statistique*, (303), 45–58.

CHAMBERLAIN, G. (1992): “Comment: sequential moment restrictions in panel data,” *Journal of Business and Economic Statistics*, 10, 20–26.

CINCERA, M. (1997): “Patents, R&D and technological spillovers at the firm level: some evidence from econometric count models for panel data,” *Journal of Applied Econometrics*, 12(3), 265–280.

COHEN, W. M. (1995): “Empirical Studies of Innovative Activity,” in *Handbook of the Economics of Innovation and Technical Change*, ed. by P. Stoneman. Basil Blackwell: Oxford, England.

COHEN, W. M., AND D. A. LEVINTHAL (1989): “Innovation and Learning: The Two Faces of R&D,” *Economic Journal*, 99(397), 569–96.

COHEN, W. M., AND D. A. LEVINTHAL (1990a): “Absorptive capacity: A new perspective on learning and innovation,” *Administrative Science Quarterly*, 35(1), 128–152.

COHEN, W. M., AND D. A. LEVINTHAL (1990b): “The Implications of Spillovers for R&D Investment and Welfare: A New Perspective,” in *Advances in applied microeconomics*, ed. by A. N. Link, vol. 5, pp. 29–45. A Research Annual Greenwich, Conn. and London: JAI Press.

COKBURN, I. M., AND R. M. HENDERSON (1998): “Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery,” *Journal of Industrial Economics*, 46(2), 157–182.

CRÉPON, B., AND E. DUGUET (1993): “Research and Developement, competition and innovation: what patent data show?,” Working Paper, N° 9314, INSEE.

——— (1997): “Estimating the Innovation Function from Patent Numbers: GMM on Count Panel Data,” *Journal of Applied Econometrics*, 12(3), 243–63.

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.

DAGHFOUS, A. (2004): "Absorptive capacity and the implementation of knowledge-intensive best practices," *S.A.M. Advance Management Journal*, 69(2), 21–27.

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

DUGUET, E., AND I. KABLA (1998): "Appropriation strategy and the use of the patent system: an econometric analysis at the firm level in French manufacturing," *Annales d'Economie et de Statistique*, 49-50, 290–327.

DUGUET, E., AND S. MONJON (2002): "Les fondements microeconomiques de la persistance de l'innovation: Une analyse econometrique. (The Microeconomic Foundations of Innovation Persistence: An Econometric Analysis. With English summary.)," *Revue Economique*, 53(3), 625–36.

ENGLANDER, A. S., R. EVENSON, AND M. HANAZAKI (1988): "R&D, Innovation and the total Factor Productivity Slowdown," *OECD Economic Studies*, (11).

FORAY, D., AND F. GAULT (2003): *Measuring knowledge management*.

GEROSKI, P. (1990): "Innovation, technological opportunity and market structure," *Oxford Economic Papers*, 42, 586–602.

GOURIÉROUX, C., A. MONFORT, AND A. TROGNON (1984a): "Pseudo maximum likelihood methods : applications to Poisson models," *Econometrica*, pp. 701–720.

——— (1984b): "Pseudo maximum likelihood methods: theory," *Econometrica*, 52(3), 681–700.

GRILICHES, Z. (1979): "Issues in Assessing the Contribution of R&D to Productivity Growth," *The Bell Journal of Economics*, 10(1), 92–116.

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

HALL, B., Z. GRILICHES, AND J. A. HAUSMAN (1986): "Patents and R&D : Is there a lag?," *International Economic Review*, 27(2), 265–283.

HALL, B., AND J. MAIRESSE (1995): "Exploring the Relationship between R&D and Productivity in French Manufacturing Firms," *Journal of Econometrics*, 65(1), 263–293.

HAUSMAN, J., B. HALL, AND Z. GRILICHES (1984): "Econometric models for Count data with an application to the patents-R&D relationship," *Econometrica*, 52(4), 909–938.

JAFFÉ, A. B. (1986): “Technological opportunity and spillovers of r&d: Evidence from firms’patents, profits and market value,” *The American Economic Review*, 76(5), 984–1001.

JIN-GUAN, D., AND L. YUAN (1991): “The integer-valued autoregressive (INAR(p)) models,” *Journal of Times Series Analysis*, 12, 129–142.

KORTUM, S., AND J. LERNER (2000): “Assessing the Contribution of Venture Capital to Innovation,” *Rand Journal of Economics*, 31(4), 674–692.

LAPLAGNE, P., AND L. BENSTED (2002): “The role of training and innovation in workplace performance,” Labor and Demography 0207005, EconWPA.

LAVOIE, M., AND P. THERRIEN (1999): “Effets de l’informatisation sur l’emploi,” Direction générale de la recherche appliquée, document de travail W-99-2F.

LEGROS, D. (2005): “Innovation, formation, qualité et performance des entreprises: une étude économétrique sur données d’entreprises,” Ph.D. thesis, Université Panthéon-Assas, Paris II.

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.

LYNCH, L., AND S. BLACK (1995): “Beyond the Incidence of Training : Evidence from a National Employers Survey,” Discussion Paper 5231, National Bureau of Economic Research, Cambridge, Ma.

MINCER, J. (1993): *Studies in human capital*. Edward Elgar.

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.

MONTALVO, J. G. (1993): “Patents and R&D at the firm level: a new look,” *Rivista Espanola de Economia*, 67, 67–81.

——— (1997): “GMM estimation of count-panel-data models with Fixed Effects and Predetermined Instruments,” *Journal of Business and Economic Statistics*, 15, 259–382.

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

PAKES, A., AND Z. GRILICHES (1984): "Estimating Distributed Lags in Short Panels with an Application to the Specification of Depreciation Patterns and Capital Stock Constructs," Discussion Paper 0933, National Bureau of Economic Research.

PETERS, B. (2005): "Persistence of Innovation: Stylised Facts and Panel Data Evidence," ZEW Discussion Papers 05-81, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

PFEIFFER, B. (1997): *Mitteilungen aus der Arbeitsmarkt- und Berufsforschung*vol. 30, chap. Determinanten von Erwerbschancen und Arbeitslosigkeitsrisiko im ostdeutschen Transformationsprozeß.

RAYMOND, W., P. MOHNEN, F. PALM, AND S. S. VAN DER LOEF (2007): "Persistence of Innovation in Dutch Manufacturing: Is it Spurious?," University of Maastricht, MERIT and CIRANO, MERIT, The Netherlands.

ROGERS, M. (2004): "Networks, Firm Size and Innovation," *Small Business Economics*, 22(2), 141–153.

ROMER, P. (1990): "Endogenous technological change," *Journal of Political Economy*, 98(5), S71–S102, part 2.

SCHERER, F. M. (1965a): "Firm size, Market structure, opportunity, and the output of patented invention," *The AZmerican Economic Review*, 55(5), 1097–1125.

——— (1965b): "Size of firm, oligopoly and Research: a comment," *Canadian Journal of Economics and Political Science*, 31(2), 255–266.

SCHULTZ, T. W. (1961): "Investment in Human Capital," *The American Economic Review*, 51, 1–17.

SCHUMPETER, J. A. (1942): *Capitalism, Socialism and Democracy*. NewYork, Harper.

SYMEONIDIS, G. (1996): "Innovation, firm size, and market structure: Schumpeterian Hypotheses and some new themes," *OECD Economic Studies*, pp. 35–70.

WINDMEIJER, F. (2002): "Expend, a Gauss Programme for Non-Linear GMM Estimation of Exponential Models with Endogenous Regressors for Cross Section and Panel Data," working Paper CWP14/02, Centre for Micro Data Methods and Practive (CEMMAP), London.

WINKELMANN, R. (2000): *Econometric Analysis of count data*. Springer.

WOOLDRIDGE, J. M. (1997): "Multiplicative panel data models without the strict exogeneity assumption," *Econometric Theory*, 13, 667–678.

A Tables of descriptive statistics and results

Table 1: Descriptive statistic for patents

Year	Means	Std. err.	Min.	Q_1	Q_2	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

Min.: minimum, Q_1: first quartile, Q_2: median, Q_3: third quartile, Max.: maximum.

Sources: Ministère de la Recherche, INPI, Céreq

Table 2: Descriptive statistic for training expenditure per employee

Year	Means	Std. err.	Min.	Q_1	Q_2	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

Min.: minimum, Q_1: first quartile, Q_2: median, Q_3: third quartile, Max.: maximum.

*: in Francs.

Sources: Ministère de la Recherche, INPI, Céreq

Table 3: Descriptive statistic for access rate to training

Year	Means	Std. err.	Min.	Q_1	Q_2	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

Min.: minimum, Q_1: first quartile, Q_2: median, Q_3: third quartile, Max.: maximum.

Sources: Ministère de la Recherche, INPI, Céreq

Table 4: Descriptive statistic for number of training hours

Year	Means	Std. err.	Min.	Q_1	Q_2	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

Min.: minimum, Q_1: first quartile, Q_2: median, Q_3: third quartile, Max.: maximum.

Sources: Ministère de la Recherche, INPI, Céreq

Table 5: Descriptive statistic for explanatory variables

Variable	Means	Std. err.	Min.	Q_1	Q_2	Q_3	Max.
R&D expenditures	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	16.19E-2	47.47E-2	3.84E-5	8.84E-4	3.23E-3	1.07E-2	6.66E-1
Clerks	0.14	0.10	0	0.08	0.12	0.17	1.00
Technicians and supervisors	0.18	0.11	0	0.10	0.15	0.23	0.70
Unskilled workers	0.19	0.21	0	2.05E-3	9.84E-2	3.36E-1	1.00
Skilled workers	0.36	0.19	0	0.21	0.35	0.51	0.96
Executives and engineers	0.12	0.08	0	0.06	0.09	0.14	0.68
Number of competitors	55.67	273.51	25	383	542	804	1360

Observations: 454

Min.: minimum, Q_1: first quartile, Q_2: median, Q_3: third quartile, Max.: maximum.

Sources: Ministère de la Recherche, INPI, Céreq

Table 6: Estimation results with the pre-sample mean estimator

	Model I		Model II		Model III		Model IV	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Intercept	-2.695**	1.413	-3.547***	1.104	-1.671	1.283	-4.422***	1.176
Number of patents $(t-1)$	-0.939***	0.139	-0.968***	0.117	-0.860***	0.110	-1.018***	0.141
R&D expenditure (log)	0.055***	0.012	0.050***	0.012	0.053***	0.012	0.052***	0.013
Training hours per employee (log)	-	-	0.304***	0.065	-	-	-	-
Access rate to training	-	-	-	-	0.234***	0.053	-	-
Training expenditure per employee (log)	-	-	-	-	-	-	0.172**	0.084
Market share (log)	-0.183**	0.074	-0.075	0.060	-0.042	0.069	-0.246***	0.053
Firm size (log)	0.774***	0.093	0.759***	0.081	0.561***	0.084	0.790***	0.067
Number of competitors (log)	0.145	0.134	0.186**	0.096	0.222**	0.105	0.209**	0.091
Executives and Engineers	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Clerks	-0.765***	0.117	-0.591***	0.094	-0.828***	0.108	-0.757***	0.118
Technicians and supervisors	-0.183	0.120	-0.027	0.091	-0.174*	0.098	-0.171*	0.103
Skilled workers	0.059	0.077	0.004	0.063	0.047	0.075	-0.174	0.120
Unskilled workers	-0.483***	0.069	-0.329***	0.068	-0.460***	0.068	-0.393***	0.069
Pre-sample information	0.358***	0.045	0.368***	0.040	0.348***	0.042	0.375***	0.041

Observations (NT) : 4430
Sources: Ministère de la Recherche, INPI, Céreq
S. E. : Robust Standard Errors
Significance levels *** : significant at 1%, ** significant at 5%, * significant at 10%