Innovations and Labour Market Institutions: An Empirical Analysis of the Italian Case in the middle 90's

Luca PIERONI - Fabrizio POMPEI*

ABSTRACT

In this paper a dynamic panel data specification is used to assess the relationship between labour market flexibility and innovation activities by distinguishing different technological regimes of activities and geographical areas of the Italian economy. In order to estimate the previous relationship, regional patents are included as a proxy of the innovation, while job turnover and wages represent labour market indicators. The results show that higher job turnover has a significant and negative impact on patent activities only in regional sectors of Northern Italy, while a positive and significant impact of blue and white collar wages has been generally found.

Key words: Labour market flexibility, Innovation, Dynamic panel data, Endogeneous relationship

J.E.L. : R12; J40; O31

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* Department of Economics, Finance and Statistics, University of Perugia.

Corresponding author: Luca Pieroni, Department of Economics, Finance and Statistics, Via Pascoli 19, 06123 Perugia; Tel 0755855280, Fax 0755855299, e-mail: lpieroni@unipg.it

1. Introduction

In the last decades, new approaches have accompanied the classical "compensation literature" in analysing the relationships between innovation and the labour market (Vivarelli and Pianta, 2000; Aghion and Howitt, 1994; Mortensen and Pissarides, 1998). In particular, the Skill-Biased Technological Changes theory (SBTC) has focused on the impact of innovations on the wages and skills of the workforce (Bound and Johnson, 1992; Berman *et al.,* 1994; Johnson, 1997, Mortensen and Pissarides, 1999; Mincer, 2003). Theoretical and empirical results have dealt with the magnitude of the shift of the relative demand for skilled labour, yielding a new equilibrium characterized by a higher relative wage and a higher share of skilled employment. According to this view, the wage inequality and the need to relax the firing and hiring restrictions in the labour market, have been seen as a direct consequence of higher innovation activities.

In the same field of studies, other authors have stressed the importance of complementarity between investments in innovation activities and the demand for skilled labour (Machin and Van Reenen, 1998; Acemoglu, 2002). If an endogenous character is recognized within this relationship, the importance of labour market regulation emerges in shaping the level and the growth rate of innovation activity (Acemoglu, 1997a). This means that labour market flexibility is conditioned by the innovation rate, but at the same time it can affect human capital investments, other than *on the job training* and *learning by doing* processes, causing feedback on innovative abilities (Acemoglu, 1997b).

On the other hand, qualitative surveys on innovations of regional economic systems have shown the importance of the labour market in performing innovation (Storper and Scott, 1995). According to these studies, labour market regulation affects the diffusion of knowledge and its mode of accumulation in the local production systems.

Moreover, some econometric analyses have explored the impact of labour market regulation on innovation, even though they do not take into account the likely endogeneity. For example

Bassanini and Ernst (2002) carried out a comparative survey among OECD countries, where the impact of product and labour market regulations on innovation is highlighted. Michie and Sheehan (2003), using a survey of UK firms, explicitly investigated firms' use of various flexible work practices and the innovative activities of those firms, within the various industrial relation systems.

Starting from these insights, the present paper aims to analyse if labour market flexibility indicators, represented by labour mobility and wages, influenced the innovation activities of Italian industries in the 1990-1996 period. In doing so, we attempted to take a step forward with respect to other empirical surveys. Firstly, a Dynamic Panel Data specification is used to include persistent behaviours in innovation, since the process is characterised by cumulative effects. Moreover, this econometric specification allows us to correct for likely spurious innovation-labour market relationships because many empirical works have shown that labour indicators are not strictly exogenous[1]. Secondly, to obtain a clear picture in shaping the link between innovation and the labour market, we have estimated a *core* framework and successfully extended econometric estimations and tests including different technological regimes (Malerba and Orsenigo, 1997; 1996) and regional development patterns (Cooke *et al.*,1997).

It is worth noting that the Italian economic debate around labour market has been particularly animated in recent years. Its lack of flexibility has often been identified as the determinant of a pathological unemployment rate which has been recognized as hindering, in advance, investments in innovations. In spite of the abundance of literature dealing with the *nexus* of the first point, we think that the second point has not been explored enough. For this reason the final purpose of our study is twofold: through clarifying some aspects of the labour market-innovation relationship in the Italian case, we wish to contribute to an overall updating of the method of empirical analysis applied to this topic.

The remainder of the paper is organized as follows. In section 2 we develop the conceptual framework supporting the empirical analysis. Section 3 focuses on the variables implemented in the econometric model and presents some descriptive statistics. Details on the econometric specifications and a brief discussion on the Arellano-Bond Dynamic Panel Data estimator are reported in section 4. Finally, in section 5 the estimated results are discussed, while final considerations are drawn in section 6.

2. The conceptual framework of empirical analysis

From a theoretical point of view the relationship between labour market flexibility and innovation has been mainly treated in the context of *Labour Turnover* (Stiglitz, 1974; Arnott and Stiglitz, 1985; Arnott *et al.,* 1988) and *Job-Search* theories (Mortensen and Pissarides, 1997; 1999) aiming to analyse the unemployment variability as the result of imbalances between flows into and out of the job market. It is necessary to remark that in the *Labour Turnover* context innovation is only tacitly considered while the focus is on the labour mobility-wage structure. A low wage causes a costly high mobility of labour that, in turn, negatively affects labour costs, productivity and human capital accumulation of workers. On the other hand, if efficiency-wage considerations emerge to solve this problem and labour market rules make layoffs prohibitively expensive, labour mobility decreases in the short term but rises in the long term. Firms cannot lay workers off, go bankrupt and an increase in unemployment level occurs.

In *Job-Search* theories, the labour market-innovation relationship is explicitly explained. According to these theories, job security reduces job destruction. The incentive to create new jobs in response to the need for changing products and production processes is reduced. For this reason too restrictive market rules inhibit an efficient reallocation of labour and hinder innovation activities.

An interesting extension of the *Job-Search models* is carried out by Acemoglu (1997a; 1997b). According to this author, when complementarities between skills of workforce and technology choice are taken into account (i.e. an economy with endogenous technology choice), a deregulated labour market is no longer the best solution. If the turnover rate increases, the firm does not invest in new technology (or R&D) and on-job training for workers, because the additional return on training, or gains stemming from acquired knowledge in R&D activities will benefit the worker who will probably soon leave the firm. On the other hand, if workers do not expect firms to invest in new technology (or R&D), their wages cannot be adequately high and they do not invest in human capital accumulation. Thus, life-time employment relationships are important factors contributing to technological changes.

The wage level can play an important role to stimulate innovation as a result of the performance of innovative and highly profitable firms. But it is not difficult to consider the equally important reverse direction of the causality. When wages are kept above their market-clearing level, regulative interventions (minimum wages, union power, normative traditions) and efficiency are involved (Shapiro and Stiglitz, 1984; Stiglitz and Greenwald, 1995). Efficiency wages exert a direct and positive effect on the active participation of the workforce in the learning process, enhancing loyalty and commitment, and stimulate practitioners into developing informal relationships, sharing information and accelerating the emergence of tacit knowledge (Antonelli, 1999; Kitson *et al.,* 2000).

As mentioned above, efficiency wages also exert a strong influence on labour mobility (lower wages stimulate skilled worker to change job), but, they very often involve unemployment (Stiglitz and Greenwald, 1995).

Empirical works have found that the impact of labour market regulation on innovation is not well defined and univocal, but rather shows different outcomes and reveals a strong context-dependent influence (Bassanini and Ernst, 2002; Michie and Sheehan, 2003). If we choose *labour mobility* and wage levels as proxies of labour market regulation[2], we can not neglect that these variables contribute to shaping the multidimensional character of *labour flexibility*. Indeed, Michie and Sheehan (2003) report a *numerical flexibility*, which is the ability of firms to change the number of people they employ. *Functional flexibility* is the ability to vary the amount of labour that firms use, without resorting to the external labour market. *Wage flexibility* is the ability of pay and payment systems to respond to labour market conditions and to reward and encourage improved performance.

In our view, these forms of *labour flexibility* could affect innovation performance of industries in different ways, depending on the one hand on their specific technological regime and on the other on the particular regional system of innovation.

Relying on various empirical works, Malerba and Orsenigo (1997; 1996) defined the technological regime of an industry as a combination of *technological opportunities*, *appropriability conditions*, *knowledge accumulation characteristics* and *base knowledge*. The analysis of the organization of innovative activities led the same authors to identify the classical Schumpeterian sectoral patterns by means of four indicators: i) localisation of innovative activities; ii) size of innovative firms; iii) permanence in the hierarchy of innovators; iv) new entry of innovators.

The *Schumpeter Mark I* pattern (SMI), defined a *creative destruction* regime, shows low concentration of innovative activities at the firm level, instability in the hierarchy of innovators and higher new entry of small business in innovation activities. Within this context knowledge spillovers among firms are relevant and the cumulative process regarding the knowledge that supports innovation occurs at the territorial level and not at the firm level. The traditional low-tech branches (food industry; textile, wear and footwear; wood and furniture; non metallic mineral products and metallic products) are highly correlated to this pattern.

Conversely, *Schumpeter Mark II* (SMII) defining the *creative accumulation* regime is reported in the same empirical analysis as the pattern where the concentration of innovative activities involves large corporations; the latter show permanence at the top of the innovators' classification and are eventually less threatened by new innovators. In this case, the accumulation of knowledge, which is more codified in nature, is supported by R&D investments and basically occurs at the firm level. Of course, there is a good correspondance between these sectors and the so-called hi-tech industries (machinery, electrical equipment, television, office machinery, medical components, motor vehicles, transport equipment).

The Regional System of Innovation (RIS) concept is developed within the theoretical context of the National System of Innovation (NIS), where parallel technological changes in work organization and production are accompanied by cultural changes or changes in habits and routines (Lundvall, 1993; Cooke *et al.*,1997; Asheim and Coenen, 2005). The shift from NIS to RIS concerns the extent of the systemic character of the geographical and administrative space considered, as well as the territorial ray of the knowledge spillover. If the tacit character of knowledge is recognized as playing a key role in innovation, the latter cannot be easily shared and applied outside from its territory of generation (Amin and Wilkinson, 1999; Antonelli, 2005). This geographical stickiness of knowledge diffusion and learning process is only one of the main characteristics of RIS. Within the latter, firms, other economic agents and local institutions co-evolve and contribute to shaping a specific political-administrative body. So RIS becomes an institutional repository of a certain negotiated, evolving, social order, that establishes routines, norms and values by which actors may come to trust each other collectively (Cooke *et al.*,1997). Different institutional settings will be likely to give rise to distinctive conventions or forms of collective social order, leading to the establishment of different kinds of organization of innovative activities, but also favouring different micro-constitutional regulations that affect the labour market.

Within this conceptual framework, the hypothesis regarding the endogenous relationship between *numerical flexibility* (or *labour mobility*) and innovative activity, can be differentiated. The numerical flexibility of the labour market can affect the innovative activities of industries and/or of regions in different ways.

In hi-tech and SMII industries, where most of the science based and scale intensive sectors are covered, it is expected that lower job turnover does not hinder the generation of innovation and/or its adoption. Knowledge accumulation at the firm level generates a strong incentive to using the firm's internal labour market (*functional flexibility*). The tenure of workforce allows not only a simple "learning by doing" process within the firm, but also guarantees a possible co-evolution among tangible assets, the firm's core competences and the workers' skills[3].

On the other hand, high turnover rates provide support for the flow of knowledge across firms, within low-tech and SMI industries. The local production systems literature highlights that small and medium sized firm sectors benefit from the dynamic labour market where skilled workers very often change their workplace (Belussi, 1999).

The different systems of governance acting at the regional level and stemming from the evolution of different socio-economical development patterns (Papagni, 1995; Cooke *et al.*, 1997) could also affect the joint behaviour of labour flexibility and innovative activities. For example, aside from technological regimes of a particular industry, higher labour flexibility could exert a different impact in regions of the South of Italy, where the problem of the adjustement of wages and mobility of labour is deemed to be more severe with respect to the North of Italy (Faini, 1997).

These arguments provide a first theoretical framework to carry out an empirical analysis where some aspects of labour flexibility and innovative activities are detected, paying attention to both the specific character of the technology underlying the different industries and the territorial features. Prior to presenting the econometric specification, a more detailed discussion on the source of data and the meaning of variables has been carried out.

3. Data sources and variables

The Dynamic Panel Data Model that will be presented in the following section concerns the manufacturing sectors of Italian industry, taken at the regional level over the period 1990-1996[4]. The relevance of the regional level has been discussed in the previous section.

As far as the variables are concerned, we chose as dependent variable patent per capita, that describes innovative activities that have occurred within a specific regional sector of industry. Patents are a measure of the innovative output and are quite "popular" among innovation scholars, even though they are not inconvenient free (Malerba and Orsenigo, 2000; Jacobsson and Philipson, 1996; Griliches, 1990). For example, the propensity to patent can vary across sectors and products (or production processess), according to institutional and structural characteristics concerning the appropriability of innovations (Malerba and Torrisi, 2000). These characteristics contribute to making the specific technological regime of the sectors, but at the same time, could severely bias the relationships to be examined. As will be discuss in section 4, the Arellano Bond estimator allows us to control this different propensity to patent across sectors.

However, it is worth noting that with respect to other indicators, such as R&D expenditures, patents often account for informal technological activity, evaluating the amount of innovative activity of medium and small firms (Malerba and Torrisi, 2000; Ferrari *et al.*, 2002). Moreover, patent data used in the present analysis come from the CRENOS databank and refer to European Patent Office (EPO) applications. This indicator should be particularly effective in taking into account potentially high remunerative innovations, which for this reason are patented abroad (Paci and Usai, 2000). Finally these patent data, initially classified by means of the International Patent Classifications (IPC)[5], have been converted to the manufacturing industry, thanks to the Yale Technology Concordance, in order to obtain coherent data with the ATECO91 classification (Paci and Usai, 2000).

As far as the *numerical flexibility* of the labour market is concerned, we chose the *gross job turnover* rate.

Actually, there is little agreement on using *gross job turnover* (or *job reallocation*) as a *proxy* for *numerical flexibility*, i.e. less hiring and firing restrictions (Bertola and Rogerson, 1997; Contini *et al.,* 1996; Boeri, 1996; 1999). In comparative analyses between European countries and US, both Bertola and Rogerson (1997) and Boeri (1999) criticize the use of turnover rate to prove the negligible differences found in flexibility terms. Conversely, they claim that high wage compression (coming from collective bargaining) and high rigidity in hiring and firing the workforce, produce high European and Italian turnover rates without the presence of real labour market flexibility. We try to take into account this objection, by introducing wage levels as explanatory variables.

Job turnover also depends on the business cycle (Schivardi 1998). We have taken into account this relationship by carrying out correlation analysis between this variable and yearly growth rate of sectoral GDP[6]. The lack of correlation confirms the result found by Boeri (1996) for Western European labour markets, where gross job turnover is basically acyclical.

In line with the aforementioned literature, we refer to *gross job turnover* as the sum of job creation and job destruction occurred at the firm level and measured by means of surveys realized by the National Institution of Social Security databank (NISS), that identify the movement of employment positions across firms.

More precisely, the average *job creation* occurring in regional sector is

$$C_{i,j} = \frac{\sum_{f} \left(E_{f,i,j,t} - E_{f,i,j,t-1} \right)}{(N_{i,j,t} + N_{i,j,t-1})/2} \qquad (1)$$

where $E_{f,i,j,t} - E_{f,i,j,t-1}$ is the positive difference between jobs registered in firm *f*, belonging to region *j* and sector *i*, over the yearly period (*t* and *t-1*);

$(N_{i,j,t} + N_{i,j,t-1})/2$ is the average number of firms belonging to region *j* and sector *i*, in which the growth of jobs occurred.

In the same way, the average *job destruction* of the regional sector is

$$D_{i,j} = \frac{\sum_{f} \left| E_{f,i,j,t} - E_{f,i,j,t-1} \right|}{(N_{i,j,t} + N_{i,j,t-1})/2} \quad (2)$$

where $\left| E_{f,i,j,t} - E_{f,i,j,t-1} \right|$ is the negative difference, taken in absolute value, between jobs registered in firm *f*, belonging to region *j* and sector *i*, over the yearly period (*t* and *t-1*).

Thus, the average *gross job turnover* in region *j* and sector *i*, is simply

$$GJT_{i,j} = C_{i,j} + D_{i,j} \quad (3)$$

Also wage levels have been drawn from NISS databank. This source allows us to differentiate between the wages of white and blue collars. Since, the white collar category includes researchers and other high-skilled workers, we can assess whether the efficiency wage effect is concentrated or not in these different worker groups.

In order to differentiate the territorial context corresponding to different models of industrialization we use, as interaction dummies, the classical five geographical macro-areas (North-West, North-East, Centre, South and the Islands). Moreover, the technological context is controlled by relying on the different intensity of R&D investment in the economic sectors, normalized by the respective GDP. The OECD classification is used to identify hi-tech/low-tech industries (Hatzichrnoglou, 1997)[7]. This international classification corresponds to the Italian classification of the R&D intensity reported by ISTAT (2001) in the Community Innovation Survey. The hi-tech/low-tech industries are considered proxies with respect to the SMII and SMI technological regimes, given the high correlation between the two categories (Pieroni and Pompei, 2003).

The ten industries, classified according to R&D intensity, are displayed in Table 1. In Table 2 some descriptive statistics on patents and labour market indicators are reported.

INSERT TABLE 1 HERE

An overall higher variability can be observed in the industry profiles of table 2. As far as the patent activities are concerned, this finding stems from the different *appropriability condition*s, which means that technological regimes matter.

The level of patent activities in some low-tech industries is not completely negligible: for example 3.18 patents per million of inhabitants in the wood and furniture sector, and 3.27 in the metal products sector are levels comparable with a high-tech sector such as that of motor vehicles (3.21). Indeed, during the nineties, there were four mature sectors (wood-furniture, textile, non metallic mineral products and metal products) in which Italy showed international specialisation in terms of patent demand (Ferrari *et al.,* 2002). There are also economic activities where the territorial location of the firms by means of industrial districts plays a key role. Taking into account this fact, we carried out an analysis restricted to these four sectors and tried to evaluate the influence of the presence of industrial districts in the innovation-labour market relationship.

INSERT TABLE 2 HERE

In the 1990-1996 period, higher average turnover rates were found in hi-tech industries and they were probably the outcome of the severe reorganization processes that took place in these industries in those years. These processes were accompanied by high standard deviation, signalling strong differences among regions.

Moreover, it is worth noting that higher wage levels, mainly within the blue collar group, did not occur in the hi-tech sectors, although it did in some low-tech sectors. Finally, it is worth noting the geographical concentration reported in empirical studies: about 56% of the demands for patents is by firms situated in the Northern Italy (Ferrari *et al.,* 2002).This fact underlines the importance of traditional historical factors that concern different models of industrialization.

4 Models and Estimations

The hypothesis that the innovation activities of Italian firms are influenced by the wages or labour mobility indicators has been investigated econometrically. This idea was also widely supported by other micro-econometric works (Chennells and Van Reenen, 1997; Flaig and Stadler, 1994; Mohnen *et al.*,1986), suggesting likely endogeneity between wages and innovations.

The first step of the estimation strategy uses a *two-way* panel data approach. In the formal way, the static panel data specification takes the following structure:

$$y_{i,t} = x_{i,t}^{'}\beta + \mu_{i,t} \qquad (4)$$

where $y_{i,t}$ is the dependent variable measuring the innovation activity, $x_{i,t}^{'}$ is the *1* ×*K* vector of explanatory variables and β is a *K* × *1* vector. We have assumed that the error $\mu_{i,t}$ follows a two-way error component model:

$$\mu_{i,t} = \mu_i + \lambda_t + v_{i,t} \qquad (5)$$

where $v_{i,t} - IID(0, \sigma_v^2)$

In particular μ_i denotes the individual-specific residual differing across sectors but constant for a given case, while λ_t year-period effects is assumed to be fixed parameters estimated as coefficients of time dummies for each year in the sample. This can be justified by macroeconomic cyclical fluctuations concerning the down-turn in the 1990-1996 period.

In order to measure the relationships between innovation activity and labour market indicators, two facts should be considered. Firstly, innovation processes are generally characterized by cumulative effects; thus, it is interesting to specify and test the existence of persistent behaviours in the innovation process by a dynamic econometric model. Secondly, the innovation process could depend on some relevant explicative variables that are not strictly exogenous, such that the unidirectional causality relationship could be questionable.

Arellano and Bond (1991) gave an answer to the first problem developing a difference GMM estimator that treats model *(4)* as a system of dynamic equations, one for each time period, in which the equations differ only in their instrument, moment condition sets and endogeneity problems. The following equation describes the dynamic specification:

$$\Delta y_{i,t} = \vartheta(y_{i,t-1} - y_{i,t-2}) + (x'_{i,t} - x'_{i,t-1})\beta + (\nu_{i,t} - \nu_{i,t-1}) \qquad (6)$$

Since $y_{i,t}$ is a function of μ_i, the lagged dependent variable $y_{i,t-1}$ is also a function of μ_i. Hence, $y_{i,t-1}$, a right-hand regressor in *(6),* is correlated with the error term, leading the OLS estimator to be biased and inconsistent. Moreover, the fixed effect estimator is biased and potentially inconsistent even if $\nu_{i,t}$ is serially uncorrelated, since $y_{i,t-1}$ is correlated with residuals (Baltagi, 2001).

Finally, the transformed equation *(6)* uses instrumental variables to estimate parameters[8] in a GMM framework in order to obtain consistent estimates if there is no second order serial correlation among errors. In particular, the assumption that the idiosyncratic error term in equation levels is not autocorrelated has two testable implications in the first-differenced equation: disturbances will exhibit negative and significant first-order serial correlations and zero second- or higher -order serial correlations.

In the Arellano-Bond estimator, Sargan's test for over-identifying restrictions and a robust version of the first step of the Arellano-Bond estimation are included to verify the adequacy of the model specification and the statistically robustness of estimated parameters for inference.

The benchmark specification, used to estimate the dynamic relationship between innovation activity and the labour market and written for simplicity in levels, is:

$$y_{i,t} = y_{i,t-1}\theta + x_{i,t}^{'}\beta + \mu_{i,t} \qquad (7)$$

where $\mu_{i,t}$ follows, as in equation *(5),* a two-way error component model. Again, μ_i denotes the individual-specific residual, differing across cases but constant for a given case. For instance, a sector with a major propensity to patent is likely to have large innovations year after year and hence have a large μ_i.

The variable $y_{i,t}$ denotes the value of innovation activity at time t (with $t = 0, \ldots, 7$), belonging to the sectoral group i[9]. According to the conceptual framework explained in section 2, we expect to find some statistically significant relationships among explanatory variables of job turnover and wage level in the innovation activity.

Given that we emphasized a plurality of hypotheses, the expected signs do not converge upon specific conjectures.

As far as turnover is concerned, the explorative nature of the analysis leads us to suppose that an overall negative sign could support the predictions of Acemoglu's model (1997a), in which the high mobility of labour hinders respectively the innovation investments of firms and human capital investments of workers. Conversely, if the result appears not statistically significant, a technological or geographical differentiation is needed in order to explore the same hypoteses in different contexts. In the context of the technological regime differentiation, we expect that a higher turnover rate affects negatively the innovative activity of the hi-tech sectors (identified with SMII technological regime), where knowledge and competences accumulate at firm level and the firms benefit from the tenure of the workforce. The opposite should happen in low-tech sectors (identified with SMI technological regime), where the creative destruction Schumpeterian pattern holds.

After a geographical differentiation, we expect the prediction of Acemoglu's model to be confirmed in the macro-area where innovative activities are more concentrated, that is in Northern of Italy.

Overall statistically significant wage levels are expected with positive signs, according to efficiency wages theory.

The explanatory variables on the right hand side of (7), also include one immediate lag of the value of innovation activity. Since the data are a collection of sectoral information, the dynamic components control the cumulative effects of innovation activities within regional sectors. In this case we do not have an *a priori* idea concerning the expected sign of these effects. Moreover, given the two-way error components, calendar year dummies are included in the estimation to control for macroeconomic impulses.

In some cases the assumption of strict exogeneity of the explicative variables is not assertable since the variables could be predetermined or endogeneous, leading to a mis-specification of the true relationship. For this reason, in order to obtain the best rationale for data, we specify wage levels (both for white and blue collars) as a predetermined variable, including the possibility that the unforecastable errors in the innovation activity (at time *t*) might affect future changes in wage levels. The literature suggested the possibility of a causal relationship between innovations and job turnover, questionable if we consider an economy with endogenous technology choice (Acemoglu, 1997a). In the empirical part we assess endogenous behaviours of the job turnover statistically, non-rejecting its endogenous specifications to depict the circular causality. From an econometric point of view, we remark that lagged levels of endogenous variables are available to serve as instruments, while the different characterization of the job turnover and wage levels as endogenous and predetermined variables, respectively, reducing the problem linked with the likely multicollinearity problem when the same labour market indicators are considered as exogenous.

The specification in equation *(7)* is used as a maintained hypothesis with the job turnover variable included as an endogenous variable and wage levels as a predetermined variable, also when we distinguish between hi-tech from low-tech technological intensity levels and macro-geographical areas.

Finally, to evaluate different impacts on innovations when the statistical parameters of labour market indicators are not significant, interaction dummies are included in equation *(7)* aiming to restrict the set of observations.

5. Results

The importance of time effects, remarked by the statistical significance of time-dummy parameters in the static specification in equation *(4),* both when white and blue collar indicators are inserted as exogenous labour market variables, stresses the need for a dynamic specification[10].

As previously mentioned, serial correlation as well as the presence of endogeneity among labour market indicators and innovation activity is solved taking into account dynamically specified models, including lagged variables on the right side of the equation. Estimation of the baseline specification of equation *(7)* by the Arellano and Bond estimator (1991) is displayed in Table 3.

INSERT TABLE 3 HERE

The two columns report estimations separately by different groups of workers using a mix of statistics for one-step and two-step estimations when we have heteroscedasticity in the data. Thus, the two-step Arellano-Bond estimator is implemented to evaluate the validity of instruments by the Sargan test since, in a one-step framework, the test is over-rejected. An overall significant dynamic specification of the model is supported by the *p-value* of the Sargan test (0.60 and 0.54 respectively) non-rejecting the included instruments. On the contrary, one-step estimations, corrected for heteroscedasticity, are used for inference on the coefficients and for testing autocorrelation higher than first-order. Thus, the null hypothesis of the first-order no-autocorrelation is rejected at the usual five percent level, while second-order no-autocorrelation is not rejected, confirming the validity of the dynamic panel data specification (Arellano and Bond, 1991).

The estimated parameters in column 1 of Table 3 suggest that only blue collar wages have a meaningful impact on patent performances of economic sectors, taken at regional level. More precisely, the higher wages of blue collars seem to improve innovative activities, whereas neither job turnover nor the cumulative effect of technology (the lagged dependent variable) play a role in this general specification. In the second column, when we replace blue collar wage levels with the white collar ones, the same result holds; we remark that the positive impact on innovative activities of the latter is slightly less stressed. Moreover, the significant influence of temporal dummies, with negative sign, underlines the role played by cyclical fluctuations. Probably the downturn period that has characterised the Italian business cycle, negatively affected R&D investment levels complementary to researchers and other high-skilled workers, included in the white collars group[11].

In Table 4, an interaction dummy has been included in the model, in order to test the sensitivity of job turnover to the geographical differentiation.

INSERT TABLE 4 HERE

Once again, both the first and second autocorrelation tests are coherent with a dynamic specification of the panel data in each equation reported below, as well as Sargan tests. In column 1, where the specification includes blue collar wages as the predetermined variable, job turnover exerts a significant and negative impact in the North-West and North-East of the country. Conversely, the same geographical interaction dummies lack statistical significance when we replace white collar wages with the blue collar ones (column 2). The significance of the results obtained for parameters in North-West and North-East regions is increased by the estimation of the equation in column 3 with a sample restricted to these areas. As expected, the conditional estimation shows a negative and statistically significant parameter for job turnover, while the robustness of the blue collars parameter is remarkable with respect to the unconditional estimation of column 1 (column 3). As mentioned in section 3, in these areas the majority of patent demands is localized. Therefore this finding is not negligible and seems to support the insights of recent views summarized in Acemoglu (1997a), in which higher mobility costs or uncertainty about the tenure of job relations negatively affect the innovation activities.

The impact of job turnover on innovation activities is not clarified by technological differentiation of industries (Table 5).

INSERT TABLE 5 HERE

The remarkable outcome of these estimations is the different behaviour of wages of each category of workers. In hi-tech industries only the blue collar wage levels influence innovative activities, acting as a sort of binding factor (column 2). Probably in this context the problem was not the lack of research, but the following set-up of the product or process to patent, carried out by qualified blue collars. Conversely in low-tech sectors the pecuniary incentive for white collars was the real binding factor (column 4), as signalled by the significance of the positive coefficient of this category. Statistically, almost all specification tests are significant. Only the Sargan test in Low-Tech industries, where blue collar wages are considered as the predetermined variable (column 3), could be questionable (p-value=0.0785). However, since the p-value is greater than the usual critical value we accept valid instruments in the estimation.

The last estimation results concern four mature sectors (textile, wood and furniture, non metallic mineral products and metal products) quoted both for relevant contributions to the technological specialisation in patent terms and for the plentiful supply of qualified workers (Ferrari *et al.,* 2002). The patent stock and flows obtained in these branches have been relevant in Italy compared with other OECD countries and have contributed to the persistence of technological specialisation in low-tech sectors. Within this context we have explored labour market-innovation relationships differentiating between the presence (or absence) of industrial districts in at least one of the four sectors, taken at the regional level. The results are illustrated in Table 6. Firstly, we can observe that job turnover is neither sensitive to particular low-tech sectors nor significant to district effects, as shown by non-significant values of the respective coefficients. Moreover, in the sample characterized by regions that include districts (column 2), it is worth noting the statistical significance of the lagged innovation variable, as well as the positive impact of white collar wages. According to the previous result concerning low-tech sectors, only the latter exert a positive impact on patents. However, the parameter size signals that in the industrial districts relative to the four sectors, white collar wages play a more important role than the whole low-tech sector group.

INSERT TABLE 6 HERE

Finally the negative impact of lagged dependent variable means that patent activities follow probably a cycle within the industrial districts of "Made in Italy".

6. Conclusions

In this paper we have investigated the impact of labour market indicators on innovative activities of Italian industrial sectors for the 1990-1996 period. Dynamic specifications of this relationship have been tested in order to account for both the presence of the innovation cumulative effects and the likely endogeneity of labour market indicators with innovation. Moreover, models including specific technological regimes of innovations and geographical areas are introduced to evaluate the likely differentiation of the relationship over these two dimensions.

The best dynamic specifications that rationalise data include wage levels as a predetermined variable and job turnover as an endogenous variable. The empirical tests confirm the circular causality discussed in the first part of the paper and it make the unidirectional causal link between labour market indicator and innovation questionable.

The results show that wage levels have a significant role in improving innovation activities. Therefore, higher wages, both in blue and white collars, stimulate the present patent activity but they are, in turn, favoured by past innovative output. This result confirms in some way the efficiency wages theory, at least as far as the determinants of innovation activities are concerned. Moreover, it is important to note the *cross significance* of wages for different worker categories, when a technological regime separation is carried out. Only blue collar wages exert a positive impact on the patent demands of hi-tech sectors, while white collar wages have a significant impact on low-tech sectors. In this context, a couple of binding factors seem to show the complementarity between different forms of knowledge that support innovation. The tacit knowledge accumulation of qualified blue collars, stimulated by higher wages, is probably crucial to develop the innovative ideas created by researchers in hi-tech firms. Conversely incentives to favour the creative participation of white collars (i.e. researchers, but also executive cadres that improve organizational aspects) are determinant in low-tech firms.

The gross job turnover, taken as indicator of labour market flexibility, has not shown an overall statistical significance. Nonetheless the result obtained through the geographic differentiation is not negligible: in regions where patent activity is more significant (the North-West and North-East of the country), labour mobility exerts a negative impact on innovation, whereas the impact the of the higher blue collar wages is positive. According to recent views that extend the job-search theory, when a negative impact on the innovative activity occurs the high mobility of labour could affect either technology investments within the firm or human capital investments carried out by workers before being hired.

Finally, in the four “Made in Italy” sectors (textile, wood and furniture, non metallic mineral products and metal products) a significant relationship holds only in the industrial districts areas. In this context job turnover does not have a significant role while, according to the result obtained in low-tech sectors, only white collar wages have a significant and positive influence. A notable finding of this case is the non cumulative character of patent activities, underlined by the significant and negative impact of the lagged dependent variable. A reasonable explanation for this kind of innovation activity, apparently contrasting the persistent technological specialisation displayed at the national level, is depicted by the Schumpeterian *creative destruction* process, occurring at the industrial districts level. In other terms the negative influence of past patent activity seems to disclose a case of strong concurrence in innovation activities among the industrial districts of "Made in Italy" sectors.

Footnotes

[1] A review on this argument is presented by Acemoglu (2002).

[2] Actually this choice is quite questionable. As we will discuss in the next section, labour mobility is often the result of an ambiguous proxy of labour market regulation. In any case there is no accordance around this point and the debate is still open. We consider this question a technical problem, related to the selection of indicators describing labour market flexibility, whereas the crucial point faced in this section concerns the consistency of the basic idea relying on the *multidimensional character* of the *labour flexibility-innovation* relationship.

[3] The crucial role played by the co-evolution of tangibile (capital, natural resources, etc.) and intangible (competencies, reputation, etc.) resources within corporations is examined by the *resource-based view* and other fields of strategic management theory (Prahalad and Hamel, 1990; Teece and Pisano, 1994; Teece, 2000).

[4]Technical problem faced by the National Institution of Social Security in updating and releasing the specific data on the labour market used in this study, constrained us to limit our analysis at this period.

[5]A system that categorizes invention by product or process.

[6] The result of our correlation analysis are available upon request to the authors. Howewer we considered the overall impact of the business cycle upon innovation-labour market relationship by introducing temporal dummies in the econometric specification.

[7] More precisely, we redefined only 2 classes, aggregating high and medium-high technology sectors in hi-tech and low and medium-low technology sectors in low-tech.

[8] It is known that valid instruments are $y_{i,t-2}$ and lagged values of $x'_{i,t}$.

[9] Obviously, the sectors are taken at the regional level.

[10] In order to save space, the results of static model (4) are not reported. The estimated results, the full data set and the program carried out with package STATA 8, are available upon request to the authors.

[11] We could not control directly for R&D investment by including them in the right side of econometric specification, because of the lack of a suitable breakdown of R&D data, involving both a sectoral and regional profile. For this reason we think that temporal dummies capture also the influence that R&D investment flows exert on patent activities.

Bibliography

Acemoglu, D. 1997a. Technology, unemployment and efficiency, *European Economic Review*, vol.41, pp.525-533.

Acemoglu, D. 1997b. Training and innovation in an imperfect labour market, *Review of Economic Studies*, vol.64, pp. 445-464.

Acemoglu, D. 2002. Technical change, inequality, and the labour market, *Journal of economic literature*, vol.XL, pp. 7-72.

Aghion, P. and Howitt, P. 1994.Growth and unemployment, *Review of Economic Studies*, vol.61, pp.477-494,.

Amin, A. and Wilkinson, F. 1999. Learning, proximity and industrial performance: an introduction, *Cambridge Journal of Economics*, vol.23, pp.121-125.

Antonelli, C. 1999. *The microdynamics of technological changes*, London, Routledge.

Antonelli, C. 2005. Models of knowledge and systems of governance, *Journal of Institutional Economics*, vol.1, pp.51-73,

Arellano, M. and Bond, S. 1991. Some test of specification for panel data: Monte Carlo evidence and an application to employment application, *Review of Economic Studies*, vol.58, pp.277-297.

Arnott R. J. and Stiglitz, J. E. 1985. Labor turnover, wage structures and moral hazard,: the inefficiency of competitive markets, *Journal of Labor Economics*, vol. 3, no. 4, pp.434-462.

Asheim, B.T. and Coenen, L. 2005. Knowledge bases and regional innovation system: comparing nordic clusters, *Research Poli*cy, vol.34, pp.1173-1190.

Baltagi, H.B. 2001. Econometric Panel Data, Wiley, Wiley College.

Bassanini, A. And Ernst, E. 2002. Labour market institutions, product market regulation and innovation: cross-country evidence, OCSE, Economic Department, *Working Papers* n. 316.

Belussi, F. 1999. Policies for the development of knowledge-intensive local production systems, *Cambridge Journal of Economics*, vol.23, pp.729-747,

Berman, E. Bound, J. and Griliches Z. 1994. Changes in the demand for skilled labour within US manufacturing industries, *Quarterly Journal of Economics*, 109(2), pp.367-398.

Bertola, G. and Rogerson, R. 1997. Institutions and labour reallocation, *European Economic Review*, vol.41, pp.1147-1171.

Boeri, T. 1996. Is job turnover countercyclical?, *Journal of Labor Economics*, vol. 14, no. 4, pp.603-625.

Boeri, T. 1999. Enforcement of employment security regulations, on the job-search and unemployment duration, *European Economic Review*, vol. 43, pp.65-89.

Bound, J. and Johnson, G. 1992. Changes in the structure of wages in the 1980's: an evaluation of alternative explanations, *American Economic Review*, 113(4), pp.1245-79,

Chennells, L. and Van Reenen, J. 1997. Technical change and earnings in British establishments, *Economica*, pp.587-604.

Contini, B. Malpele, C. and Villosio, C., 1996. Wage dynamics and labour mobility in Italy, *Quaderni di Ricerca 96*, n.06, Dipartimento di Economia, Università di Torino,

Cooke, P. Gomez Uranga, M. and Etxebarria, G. 1997. rRgional innovation systems: institutional and organizational dimensions, *Research Policy*, vol.26, pp. 475-491,

Faini, R. 1997. Trade unions and regional development, Centro Studi d'Agliano, *Working Papers*, n.115,.

Ferrari, S. Guerrieri, P. Malerba, F. Mariotti, S. and Palma, D. 2002. L'Italia nella competizione tecnologica internazionale. Terzo rapporto, Milano, Franco Angeli.

Flaig, G. and Stadler, M. 1994. Success breeds success: the dynamics of the innovation process, *Empirical Economic*, vol. 19, pp.55-68.

Griliches, Z. 1990. Patent statistics as economic indicators: a survey, *Journal of Economic Literature*, Vol. XXVIII, pp.1661-1707.

Hatzichronoglou, T. 1997. Revision of the Hi-Technology sector and product classification, *OCDE STI Working Papers*, no. 2.

Istat (2001), Statistiche sull'innovazione tecnologica, Roma.

Kitson, M. Martin R. and Wilkinson F. 2000. Labour markets, social justice and economic efficiency, *Cambridge Journal of Economics*, vol.24, pp.631-641.

Jacobsson, S. and Philipson J. 1996. Sweden's technological profile. What can R&D and patents tell and what do they fall to tell us, *Technovation*, vol.26, pp.245-253.

Jonson G. 1997. Changes in earnings in equality: the role of demand shifts, *Journal of Economics Perspectives, vol.*11, pp.41-54,.

Lundvall B. A. 1993. National *Systems of Innovation*, London, F. Pinter Publishers.

Malerba, F. and Orsenigo, L. 1996. Schumpeterian patterns of innovation are technology specific, *Research Policy*, vol.25, pp. 451-478.

Malerba, F and Orsenigo L. 1997. Technological regimes and sectoral pattern of innovative activities, *Industrial and corporate change*, 6, I, pp. 83-117,

Malerba, F and Orsenigo, L. 2000. Replay to letter to the editor regarding paper "Technological entry, exit and survival: an empirical analysis of patent data", *Research Policy*, vol. 29, pp.1187-1188,.

Malerba, F. and Torrisi, S. 2000. La politica pubblica per l'innovazione, in Malerba F. (eds) *Economia dell'innovazione*, Roma,Carocci editore.

Machin, S. and Van Reenen J. 1998. Technology and changes in skill structure: evidence from an international panel of industries, *Quarterly Journal of Economics*, 113(4), pp.1215-44.

Michie, J. and Sheehan, M. 2003. Labour market deregulation, "flexibility" and innovation, *Cambridge Journal of Economics*, vol. 27, pp.123-143.

Mincer, J. *2003.* Technology and the labour market, *Review of Economics of the Household, vol.1, pp.249-27,.*

Mohnen, P.A. Nadiri, M.I. and Prucha, I.R. 1999. R&D, production structure and rates of return in the US, Japanese and German manufacturing sectors, *European Economic Review*, vol. 40, pp.381-401.

Mortensen, D.T. and Pissarides, C.A. 1994. Job creation and Job destruction in the theory of unemployment, *Review of Economic Studies,* vol.61, pp.435-456.

Mortensen, D.T. and Pissarides, C.A. 1998. Techonological progress Job creation and Job destruction, *Review of Economic Dynamic,* vol.1, pp.733-753,

Mortensen, D.T. and Pissarides, C.A. 1999. Unemployment responses to “skill biased technology shocks: the role of labour market policy, *Economic Journal,* 109, pp.242-265.

Paci, R. and Usai, S. 2000. The role of specialisation and diversity externalities in the agglomeration of innovative activities, *Rivista Italiana degli Economisti*, no. 2.

Papagni, E. 1995.*Sviluppo rurale e progresso tecnico nell’economia italiana*, Milano, Franco Angeli.

Pieroni, L. and Pompei, F. 2003. Localizzazione geografica delle innovazioni e mercato del lavoro, paper presented at XXIII Regional Sciences Italian Conference, Perugia, october 7-8, forthcoming in Rivista di Politica Economica.

Prahalad,C.K. and Hamel G. 1990. The core competence of the corporation, *Harvard Business Review*, vol.68, pp.79-91.

Shapiro, C. and Stiglitz, J. E. 1984. Equilibrium unemployment as a worker disciplining device, *American Economic Review*, vol.LXXIV, pp.433-44.

Schivardi, F. 1998. Reallocation and learning over the business cycle, *Banca d’Italia, Temi di discussione, no.345.*

Stiglitz, J. E., 1974. Alternative theories of wage determination and unemployment in LDC's: the labour turnover model, *The Quarterly Journal of Economics*, vol.88, no.2, pp.194-227.

Stiglitz, J. E. and Greenwald B.C. 1995. Labor-market adjustements and the persistence of unemployment, *American Economic Review*, 85, pp. 219-225.

Storper, M. and Scott, A.J. 1995. The wealth of regions, *Futures*, vol.27, no. 5, pp.505-526.

Teece, D.J. and Pisano, G. 1994. The dynamic capabilities of the firm: an introduction, *Industrial and Corporate Change*, 3, pp.537-556,

Teece, D.J. 2000. Strategies for managing knowledge Assets: the role of firm structure and industrial context, *Long Range Planning*, vol.33, no.1, pp.35-54.

Vivarelli M. and Pianta M., (eds) 2000. *The employment impact of innovation. Evidence and policy*, London, Routledge.

TABLES

Table 1 – Industries and their technological intensity

Industry	Technological intensity	
	HI-TECH	LOW-TECH
Food, beverages and tabacco		●
Textile products, Wear industry, Leather industry; Luggage, handbags and footwear		●
Wood, Forniture and other manufacturing		●
Paper, printing and publishing		●
Coke and refined petroleum products, Chemical products and synthetic fibres, Plastic products	●	
Non metallic mineral products		●
Fabricated and structural metal products		●
Machinery, electrical equipment, television, office machinery, Medical components and Instruments for measuring	●	
Motor vehicles, Transport equipment	●	
Building		●

Table 2 - Summary statistics by industry (average 1990-1996)

	Patents per million Inhabitants				Turnover			
	Sum	Dvst	Min	Max	Mean	Dvst	Min	Max
Food, beverages and tabacco	0.36	0.03	0.00	0.21	4.45	0.70	3.49	6.92
Textile products, Wear industry, Leather industry; Luggage, handbags and footwear	1.24	0.10	0.00	0.52	5.61	0.90	3.48	9.96
Wood, Forniture and other manufacturing	3.18	0.17	0.00	0.61	4.76	1.94	3.41	25.13
Paper, printing and publishing	0.62	0.04	0.00	0.19	4.51	0.70	2.53	6.31
Coke and refined petroleum products, Chemical products and synthetic fibres, Plastic products	11.03	0.66	0.00	3.10	7.29	2.12	4.47	14.52
Non metallic mineral products	0.68	0.04	0.00	0.32	5.41	1.04	3.58	10.15
Fabricated and structural metal products	3.27	0.18	0.00	0.60	5.75	1.47	3.94	11.71
Machinery, electrical equipment, television, office machinery, Medical components and Instruments for measuring	32.15	1.74	0.00	6.27	6.35	1.51	3.75	13.79
Motor vehicles, Transport equipment	3.21	0.25	0.00	1.38	14.97	17.92	2.00	121.67
Building	0.12	0.01	0.00	0.04	5.33	0.84	3.55	7.52
	Blue collar wages				White collar wages			
	Mean	Dvst	Min	Max	Mean	Dvst	Min	Max
Food, beverages and tabacco	28506	2890	22720	34663	35011	5231	25088	47479
Textile products, Wear industry, Leather industry; Luggage, handbags and footwear	23240	2271	18959	28060	27767	6243	16176	41131
Wood, Forniture and other manufacturing	24757	2317	19751	29143	30604	3873	22116	38461
Paper, printing and publishing	27375	3113	21509	36566	32078	5036	19809	44581
Coke and refined petroleum products, Chemical products and synthetic fibres, Plastic products	24964	2652	15832	30302	32534	4230	24601	46942
Non metallic mineral products	27804	2738	22059	34099	34027	4581	24636	47990
Fabricated and structural metal products	28005	3155	22324	34485	33788	5701	23314	46046
Machinery, electrical equipment, television, office machinery, Medical components and Instruments for measuring	25421	3085	19007	34004	32306	4508	23422	45972
Motor vehicles, Transport equipment	26771	3333	12896	33657	30915	8248	7829	45987
Building	30916	2172	25570	35019	35147	2978	28153	42635

Table 3 – Estimation of baseline specifications

Dependent Variable: Patents	(1)	(2)
Patents $_{(t-1)}$	-0.1828*	-0.1944
	(-1.18)	*(-1.21)*
Turnover	0.0007	0.0008
	(0.61)	*(0.72)*
Blue collars wages	0.0161	
	(2.42)	
White collar wages		0.0004
		(2.41)
Time Dummy 1993	-0.0418	-0.0427
	(-2.80)	*(-2.91)*
Time Dummy 1994	-0.0494	-0.0665
	(-1.78)	(-2.40)
Time Dummy 1995	-0.0601	-0.0799
	(-1.43)	*(-1.93)*
Time Dummy 1996	-0.1038	-0.1255
	(-1.93)	*(-2.38)*
Constant	0.0066	0.0177
	(0.47)	*(1.50)*
Arellano Bond test Ho: non-autocorrelation (first order)	z=-2.09 (0.036)	z=-1.89 (0.059)
Arellano Bond test Ho: non-autocorrelation (second order)	z=-1.03 (0.304)	z=-1.10 (0.271)
Sargan test (Prob>χ^2)	(0.6009)	(0.5432)

*z value in brackets

Table 4 - Estimation by territorial differentiation

Dependent Variable: Patents	(1)	(2)	(3) *Sub sample North-West and North-East*
Patents $_{(t-1)}$	-0.1833*	-0.1954	-0.0486
	(-1.19)	(-1.22)	*(-0.43)*
Turnover	0.0002	0.0022	-0.0029
	(0.24)	*(0.85)*	*(-1.94)*
Blue collars wages	0.0172		0.0435
	(2.48)		*(2.89)*
White collar wages		0.0051	
		(2.84)	
NorthWest*turnover	-0.0021	-0.0036	
	(-2.46)	-*(1.42)*	
NorthEast*turnover	-0.0020	-0.0037	
	(-2.17)	(-1.37)	
Centre*turnover	0.0349	0.0025	
	(0.36)	*(0.25)*	
South*turnover	0.000001	-0.0034	
	(0.00)	-*(1.11)*	
Time Dummy 1993	-0.0425	-0.0438	-0.0713
	(-2.79)	(-2.94)	(-2.32)
Time Dummy 1994	-0.0466	-0.0649	-0.0980
	(-1.69)	(-2.36)	*(-1.57)*
Time Dummy 1995	-0.0601	-0.0812	-0.1075
	(-1.43)	(-1.96)	*(-1.12)*
Time Dummy 1996	-0.1032	-0.1253	-0.2482
	(-1.90)	(-2.36)	*(-2.02)*
Constant	0.0056	0.0169	-0.0012
	(0.40)	(1.44)	*(-0.04)*
Arellano Bond test *Ho*: non-autocorrelation (first order)	z=-2.07 (0.038)	z=-1.85 (0.064)	z=-2.37 (0.018)
Arellano Bond test *Ho*: non-autocorrelation (second order)	z=-1.07 (0.285)	z=-1.15 (0.248)	z=-1.27 (0.202)
Sargan test (Prob>χ^2)	(0.6194)	(0.6008)	(0.2222)

**z value in brackets*

Table 5 - Estimation by technological intensity of industries

	Hi-Tech sectors		Low-Tech sectors	
Dependent Variable: Patents	(1)	(2)	(3)	(4)
Patents $_{(t-1)}$	-0.8761	-0.1250	-0.097	-0.1167
	(-0.65)	*(-0.83)*	*(-1.08)*	*(-1.39)*
Turnover	-0.0001	0.0006	-0.0021	-0.0004
	(-0.10)	*(0.58)*	*(-0.45)*	*(-0.11)*
Blue collars wages	0.0232		0.0123	
	(2.51)		*(1.59)*	
White collar wages		0.0004		0.0003
		(1.18)		*(2.19)*
Time Dummy 1993	-0.1482	-0.1320	-0.0086	-0.0115
	(-2.65)	*(-2.60)*	*(-1.12)*	*(-1.71)*
Time Dummy 1994	-0.1779	-0.2001	-0.0028	-0.1506
	(-1.96)	*(-2.17)*	*(-0.27)*	*(-1.75)*
Time Dummy 1995	-0.2561	-0.2718	0.0061	-0.0093
	(-1.89)	*(-1.98)*	*(0.39)*	*(-0.85)*
Time Dummy 1996	-0.4006	-0.4128	-0.0019	-0.0189
	(-2.34)	*(-2.43)*	*(-0.09)*	*(-1.19)*
Constant	0.06413	0.0766	-0.0114	-0.0026
	(1.77)	*(2.12)*	*(-1.08)*	*(-0.57)*
Arellano Bond test Ho: non-autocorrelation (first order)	z=-2.57 (0.010)	z=-2.20 (0.028)	z=-3.04 (0.002)	z=-3.23 (0.001)
Arellano Bond test Ho: non-autocorrelation (second order)	z=-0.64 (0.521)	z=-0.79 (0.428)	z=-1.28 (0.199)	z=-1.43 (0.152)
Sargan test (Prob>χ^2)	(0.2354)	(0.4070)	(0.0785)	(0.5179)
*z value in brackets				

Table 6 - Low-tech sectors that displayed patents specialisations

	Regions with districts		**Regions without districts**	
Dependent Variable: Patents	(1)	(2)	(3)	(4)
Patents $_{(t-1)}$	-0.1282	-0.2091	-0.1625	-0.1294
	(-1.72)	*(-2.59)*	*(-1.33)*	*(-0.98)*
Turnover	-0.0054	-0.0028	-0.0013	0.0013
	(-0.53)	*(-0.33)*	*(1.15)*	*(0.97)*
Blue collars wages	-0.0004		0.0001	
	(-0.38)		*(0.34)*	
White collar wages		0.0006		0.0001
		(2.42)		*(0.50)*
Time Dummy 1993	-0.0310	-0.0312	0.1172	0.0116
	(-2.00)	*(-2.10)*	*(1.43)*	*(1.33)*
Time Dummy 1994	-0.0103	-0.0456	0.0056	0.0046
	(-0.43)	*(-2.25)*	*(0.60)*	*(0.48)*
Time Dummy 1995	0.0026	-0.0304	-0.0007	-0.0015
	(-0.09)	*(-1.21)*	*(-0.06)*	*(-0.11)*
Time Dummy 1996	-0.1592	-0.0457	-0.0015	-0.0022
	(-0.41)	*(-1.24)*	*(-0.08)*	*(-0.11)*
Constant	0.0089	-0.0873	0.00002	-0.0005
	(0.62)	*(-0.88)*	*(0.00)*	*(0.10)*
Arellano Bond test Ho: non-autocorrelation (first order)	z=-2.90 (0.004)	z=-2.50 (0.012)	z=-1.82 (0.068)	z=-1.78 (0.074)
Arellano Bond test Ho: non-autocorrelation (second order)	z=-1.74 (0.081)	z=-1.57 (0.116)	z=-0.01 (0.991)	z=0.19 (0.849)
Sargan test (Prob>χ^2)	(0.722)	(0.625)	(0.978)	(0.985)

*z value in brackets