Flexible Labour and Innovation in the Italian Industrial Sector*

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Abstract

In this paper we study how labour flexibility within firms affects innovation. Using data from the Bank of Italy's yearly survey of Italian industrial and service firms and information on patent applications collected by the European Patent Office, we find that innovation falls when firms increase the share of temporary workers. The negative effect of labour flexibility is found both on the yearly probability of submitting a patent application and on the number of applications per year and it is larger for firms operating in high-tech industries. The identification of the causal effect of interest relies on a series of policy changes that modified the relative cost of temporary employment.

The negative effect of labour flexibility on innovation may be due to the willingness of firms to trade future productivity gains (due to innovation) with a lower current labour cost. As a consequence, by reducing the cost and protection of temporary employment, reforms of the labour market introduced in the country since the end of the 1990s may have been a determinant of the low innovation activity of Italian industrial firms.

Keywords: Innovation, Patents, Temporary employment.

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1 Introduction

The innovation gap between Italy and other developed countries has stimulated recent research aimed at disentangling the main determinants of innovation. Several factors explain the low capability of Italian firms to produce innovation (Bugamelli et al. (2012) for a taxonomy). Among these factors there are institutional features of the Italian economy, such as the structure of the credit market, and characteristics of firms, such as their small size. We contribute to this literature by studying how the composition of the firms' labour force in terms of permanent and temporary employment modifies their innovative activity. How this channel works has so far received little attention, but the rapid increase of temporary forms of employment in Italy and in other European countries makes an understanding of it important.

The steady diffusion of temporary contracts is a major fact of the last decades for most European countries; Italy stands out in this respect. It features a relatively low incidence of temporary positions - about 13 per cent of payroll employees are temporary - and its labour market is often considered as being heavily regulated, but the proportion of temporary positions has grown more than in the majority of European countries during the last ten years (OECD, 2012). Moreover, a large share of the inflow into employment is attributable to temporary jobs: the Italian National Office of Statistics reports that between 2005 and 2010 temporary positions accounted on average for 71.5 per cent of new jobs in big manufacturing firms (Istat, 2012a). Temporary jobs are uneavenly distributed across generations. In particular they are concentrated among workers under 30: one third has a temporary job (Istat, 2012b).

In this paper we study how labour flexibility within firms affects innovation by focusing on numerical flexibility. Numerical flexibility is the capability of a firm to adjust employment in response to the business cycle and to idiosyncratic shocks. However, it does not represent the only form of labour flexibility at the firm level. Beatson (1995) points out that flexibility also relates to firms' ability to reallocate workers to different tasks (functional or internal flexibility) and to adjust wages easily in response to shocks on productivity (wage flexibility).

In our analysis we use patent applications as a measure for innovation. Clearly, this is not the only possible one, and it is not even the one most commonly used. Other measures have frequently been adopted, too: for instance the share of sales of innovative (or new) products (Crepon et al., 1998; Zhou et al., 2011) or self-reported measures of engagement in R&D (Becker and Egger, 2007; Zhou et al., 2011; Griffith et al., 2006). The use of the number of patent applications as a measure of innovation has advantages and disadvantages that are well known in the literature (Marin, 2012). Firstly, for the area of interest, Italy, information is available for the universe of patent applications. Secondly, they represent a hard measure of innovation, being immune from self-reporting bias, as they result from a standardized acceptance procedure conducted by external evaluators. Since in our analysis we study the innovative activity of Italian firms, the external evaluator is the European Patent Office (EPO). The use of patent applications can however be problematic since they only capture the output of the innovation process and do not inform on the resources that a firm has invested to achieve it[1]. Moreover, they only cover a subset of all innovations, since not all discoveries are patented. A problem that arises when studying innovation through patent data is that they often need to be complemented with other information on the applicant firms, and this usually requires matching with additional data sets. We complement the EPO Patstat data set by using firm level data captured by the Bank of Italy's survey of a sample of Italian industrial and service firms.

Our results suggest that there exists a statistically significant and negative relationship between the proportion of temporary workers and the innovation of Italian firms. This negative relationship is found both on the yearly probability of submitting at least one patent application (extensive margin) and on the number of applications submitted in a year (intensive margin). When innovation and flexibility move in opposite direction, as we find, high flexibility further reduces innovation below a level which is already socially inefficient as a consequence of positive externality in innovation. Since the proportion of temporary workers is endogenous with respect to other firms' choices, we exploit a policy change modifying the relative cost of temporary workers to instrument our measure of flexibility. The policy consists in a tax credit for permanent hires introduced in Italy in 2001 (the so called "bonus occupazione").

We also test whether the effect of labour flexibility is the same for firms operating in high and low-tech industries. We find that lowering the quality of employment, through a higher proportion of temporary workers, reduces innovation significantly among high-tech firms, whereas it produces only small effects among the other firms. This may reflect the fact that the skill gap between permanent and temporary workers is narrower in low-tech industries, where labour is on average unskilled. Additionally, for high-tech firms, an increase in flexibility may result in a larger reduction of innovation because in these firms a higher fraction of workers is devoted to innovation, whereas, in low-tech firms, the same increase would be spread over workers that are not involved in the production of innovation.

Since the mid 1990s the reforms of the Italian labour market have intensively affected the relative cost of temporary and permanent employment, making the former less protected (figure 1). One of the main goals of these reforms was to reduce the firms' cost of adjusting the labour force and to increase the overall labour market participation. If permanent employment fosters innovation - as our statistical analysis indicates -, then these kinds of policies may have had a negative effect on innovation and on growth, by making temporary employment less costly.

[1] This does not imply that input in innovation is necessarily a better measure of innovation as a large input with low output might simply indicate that resources have been wasted by the firm.

Fig. 1. Ratio of temporary on permanent worker protection indices

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The paper is organized as follows: In the next section we briefly outline the relevant literature; in the third one we describe our data. Section 4 is devoted to illustrating the main features of the policy we use as the exogenous source of variation for numerical flexibility. Section 5 presents the main results on both the intensive and extensive margin, together with a discussion on possible interpretations of the results. Section 6 concludes.

2 Literature

On theoretical grounds, labour flexibility affects innovation through several channels. The theory predicts that some of these channels have a positive effect of flexibility on innovation, other channels imply negative effects. Moreover, the relation can possibly run in the other direction, with innovation affecting the type of labour demanded by firms (Malgarini et al., 2012).

Most of the literature has interpreted the relation of flexibility and innovation as spurring from the link between the former and labour productivity. In turn, the effect of temporary employment on productivity has been interpreted by looking at differences into skills and incentives across workers employed on different contracts. Following the literature, the relation between productivity, innovation and flexibility can be briefly described in the following way. In the short run a flexible workforce assures a lower adjustment cost of labour demand in response to shocks, and this may result in a positive correlation between innovation and flexibility. In the long run, however, an extensive use of temporary workers may imply lower incentives for firms and employees to invest in human capital, causing a reduction of innovation and future productivity. Therefore, our work aims at determinining whether the sign of the net effect of these two forces acting in opposite directions is positive or negative. In this section we review the main studies that address the relation among productivity, innovation and of labour flexibility. We divide our discussion in two strands of literature. According to the first one the lack of labour market flexibility can be detrimental for innovation, whereas the second one includes studies discussing reasons why more labour flexibility should be associated to more innovation.

A flexible labour market can increase the propensity of firms to innovate. Firms are often hit by technological and demand shocks generating large flows of job creation and destruction. Firms' productivity crucially depends on how easily and how quickly they can respond to these shocks. Therefore, restrictions on the reallocation process of labour reduce firms' average productivity (Hopenhayn and Rogerson, 1993), and together with the effects of other labour market institutions, such restrictions can affect firms' incentives to innovate (Bassanini and Ernst, 2002). For instance, the presence of a stringent Employment Protection Legislation (EPL) and of high firing costs can push an economy toward sectors where technology progress slowly and demand is stable. Samaniego (2006) shows that the effect of labour market regulations is stronger on industries experiencing fast technological changes. In these industries, in fact, firms need to change the employment level more frequently since they tend to rapidly fall behind in technology. Therefore, when EPL is tight firms are less likely to operate in industries hit by frequent technological shocks. Overall this may result in an economy specialized in industries where technological change is sluggish. A similar argument about demand shocks is provided by Saint-Paul (2002), which points out that a rigid labour market can increase the production of goods with a stable demand, that usually are in the late stage of their lifecycle. This can translate in a reduction of innovation at the aggregate level. Italy seems to have both these characteristics: specialization in industries where large technological shocks are rare and in industries where demand is stable. In Italy innovation is often small or incremental (so called secondary innovation) and the development of new products and technology is quite rare (Bugamelli et al., 2012). This is also witnessed by the share of innovating firms in manufacturing, which is not different from the rest of Europe, even though Italy is far behind its competitors in terms of investments in R&D and propensity to patent.

Flexibility also modifies employees' incentives and their bargaining power, affecting their effort on the job. Permanent workers may in fact be more easily shirking, since firing is unlikely to be a credible threat. Along these lines, Jacob (2010) and Ichino and Riphahn (2005) show that a lower employment protection can increase productivity through the reduction of absenteeism. The higher bargaining power of permanent workers may result in higher wages and in less resources devoted to investment and innovation, especially when firms are credit constrained (Malcomson, 1997; Zhou et al, 2011).

The previous discussion points out that flexibility, productivity and innovation can move in the same direction. Other mechanisms however suggest that a higher demand of temporary workers reduce the ability of a firm to innovate. According to this view, temporary workers display on average a lower level of general and firm specific human capital. Firms with a high labour turnover may lack of historical memory and of knowledge of markets (Zhou, 2011) and this could weaken their innovation. Moreover, given the hold-up problem that is typical of fixed-term employment relationships, firms invest less on the development of skills of temporary workers.

The lower level of human capital of temporary workers is not the only way flexibility can be harmful for innovation. Another mechanism is related to the fact that the effort produced by workers is not perfectly observable. Therefore, fixed term employees can be particularly prone to exert low level of effort if they expect to be fired (not renewed) at the end of their contract (Bentolila and Dolado, 1994). Moreover firms can be reluctant to innovate when they fear that temporary employees are likely to share with competitors sensitive information.

The causal relation between R&D and flexibility also runs in the other direction, with the choice of investing in R&D affecting the workforce composition. When firms are engaged in innovative activity, they typically show high but highly volatile expected profits. In this situation, temporary employment is a form of insurance for the firm against negative shocks. In fact, the expected cost due to large and negative technology and demand shocks can be reduced by hiring workers that can be cheaply dismissed, even if this may come to the cost of lower productivity of labour. According to Lotti and Viviano (2012) the reduced productivity of temporary workers that firms are willing to accept can be seen as the price of a real option allowing firms to adjust labour when needed. Along similar lines, Adessi et al. (2012) show that innovative firms actually face two opposite incentives to hire temporary workers. On the one hand they require less labour flexibility since the probability of dismissal decreases with high expected profits. On the other hand innovative firms need more temporary workers to offset profit volatility. According to their estimates, the second force prevails, generating a positive correlation between innovation and flexibility.

3 Data and Descriptive Statistics

To perform our analysis we use two sources of information. The first data set, *"Indagine sulle imprese industriali"* (Invind) conducted by the Bank of Italy, contains detailed information on Italian manufacturing firms. The survey is collected on a yearly basis on about 3,000 Italian firms with at least 20 employees. Since 2001 the survey includes questions on the firms' workforce, on the number of newly hired and fired workers and on the number of temporary employees.

The second source of information that we use is the Worldwide Patent Statistical Database (Patstat) collected by the EPO, that includes information on firms' patent applications, such as, the applicant's name, its address, the application and priority dates. Linking each patent application to the firm that made the submission is however not immediate, since a univocal identifier for the applicant is lacking. Marin (2012) exploits exact and approximate matching techniques to recover the fiscal code of the applicant firm, obtaining a list of fiscal codes and patent applications. The large proportion of observations with missing information, the presence of typos on firm's name and location and other features of Patstat (see Marin (2012) for a discussion) makes it impossible to produce a perfect matching. Nevertheless, from 2001 to 2009, about 90% of patents from the EPO database have been matched to Italian firms, using fiscal codes by the Bureau van Dijk Aida database and Marin's algorithm. We use this list of fiscal codes to match Patstat data with Invind since, to our knowledge, there is no better source for that information.

The data that we use for our analysis is not representative of the whole population of Italian manufacturing firms. We limit our analysis to firms over 49 employees since important information, such as the firm expenditure in R&D, is lacking in Invind for small firms in some years.

In the sample of firms with at least 50 employees selection issues can be related to the merging procedure that we adopted to construct the final data set. To this extent, selection could be a relevant problem only if among the patent applications that Marin (2012) did not manage to link to a firm (about 10 per cent between 2001 and 2009) applications by Invind firms were not random. In other words, selection can be harmful in our data if innovative firms in Invind that are not included in Aida (i.e. whose fiscal code had not been recovered) are statistically different from innovative firms in Invind that are included in Aida. This possible source of selection seems however to be unlikely in our data.

We start by describing the data set of matched patent applications. We match roughly 7,500 Patstat patent applications to their applicants (i.e. firms that are in Invind) from 2001 to 2008 (table 1). We discard patent applications recorded before 2001 for two reasons. First, before that year the quality of the matching of patent application to fiscal codes is lower. Second, some variables that are crucial for our analysis had not been collected before 2001 in Invind. The number of matched patents increases until 2005, then decreases in the consequent years. The significant drop registered in 2008 and even more in 2009 is likely due to the delay in the publication of patent applications in the EPO database (Hall et al. 2001). For this reason, we restrict our analysis to years 2001-2008.

Tab. 1. Patents applications and shares by year and area in the matched data set

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In order to make more transparent how distortions due to the use of a sub-sample of all patent applications can affect the results, table 1 can be compared to table 2. Table 1 shows the marginal distribution of patent applications by year and area in our final data set, after matching Patstat data with firms fiscal codes and Invind. Table 2 reports the original distribution in Patstat (original administrative data). This table shows that on average, between 2001 and 2008, 47.1 per cent of the applications had been submitted by firms located in the North West of the country (49.6 in the matched data). Only less than the 4 per cent of them can be attributed to firms located in Southern regions (2.7 in the matched data). Overall, such territorial distribution appears to be stable over time.

Tab. 2. Patents applications and shares by year and area in Patstat

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Table 3 shows the fraction of all patents in Patstat that are assigned to a firm in Invind. Table 3 provides such coverage share by year and geographic area. On the whole sample, the average coverage is 25.0 per cent. At the beginning of our period of interest, only 21.1 per cent of patent applications are matched to a Invind firm. In 2005 such share reaches its maximum (30.4 per cent), then it declines at around 24 per cent. Looking at geographic areas, the coverage is higher in the Central regions of Italy and in the North West, where the headquarters of most large companies are often located. In the North East, where innovative firms are more likely to be small, the coverage share is lower. It is worth to remark that the coverage rate is low by construction and not because of poor matching. In fact, while Patstat comes from administrative data and it represents the universe of all patent applications, Invind is a survey on a fraction of Italian industrial firms.[2] Thus, even in the absence of other issues, full coverage is not feasible.

Tab. 3. Coverage shares in the matched data set

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Table 4 shows the distributions of firms in the sample with respect to their industry and area. We divide firms in innovative and not innovative. By innovative, we mean firms that presented at least one patent application in the entire period of interest (2001-2008). According to this definition, 10.5 per cent of firms can be classified as innovative. This share turns out to be higher in the mechanical and in the chemical sector (respectively 15.9 and 14.1 per cent) and lower for firms in food and textile industries (1.7 and 3.6 per cent). The share of firms that presented a patent application in the corresponding year is 5.5 per cent, ranging from 8.5 per cent in the mechanical and 1.2 per cent for firms in the food industry. As for patents, almost half of the innovative firms are located in the North West of the country, where innovative firms represents 12.5 per cent of the sample. In the South, only 3.0 per cent of firms had on the contrary applied for a patent during the reference period.

Tab. 4. Innovative and not innovative firms by sector and area

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The average number of applications in the entire sample is 0.20 per year (table 5). Focusing only on innovative firms it increases up to 3.7. The average number of applications is similar in the North and Centre of the country, but remarkably lower in the South. The intensity in the application process is higher in the Centre of the country, where innovation seems to be concentrated in fewer but bigger companies: in this area, the average number of applications for innovative firms is 4.62 (it only reaches 2.14 in the South). As for the extensive margins,

[2]Nevertheless appropriate weights guarantee that Invind represents the population of interest.

firms in the chemical and mechanical sector also apply for more patents on average and conditional on being innovative.

Tab. 5. Descriptive statistics: patents application per year, area and sector

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As shown in table 6, innovative firms are on average roughly 4 times bigger in terms of turnover (208 millions of euros versus 58 millions, 45 versus 18 at the median) and 3 times bigger in terms of employees (515 versus 166 units, 185 versus 90 at the median). They are also more productive in terms of turnover per employee. As expected, they display a higher level and propensity to export and to invest in R&D. On the contrary, the share of temporary workers is higher among not innovative firms: 6.1 per cent, 0.7 percentage points more than among innovative firms. Nevertheless, the difference in the shares is not significant at 5 per cent level.

Tab. 6. Descriptive statistics: Covariates

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4 Temporary Employment and Policy Reform

In Italy, as well as in most OECD countries, permanent contracts are the most common form of employment. On top of not having a termination date, permanent jobs entail stringent protection for the worker, usually achieved by high firing costs for the employer. Temporary contracts are on the other hand designed to satisfy specific or temporary needs of the employer: in particular, the Italian legislation establishes that fixed-end employment is allowed for technical reasons, such as the temporary need of a worker with specific skills, for productive reasons (temporary peaks in production) or for the substitution of an absent worker. Temporary contracts can be renewed, but only under special circumstances and with significant limitations. However, in practice, most of these principles have not been widely enforced.[3]

Until the end of the 1990s, temporary contracts represented a low share of total employment and they were mostly concentrated in the agricultural industry, as a consequence of its seasonality. The reform of temporary employment, embodied in the Law 368/2001, made easier for firms to hire fixed-end workers, contributing to their rapid diffusion. The loosening

[3] The recent reform of the labour market, the so called "Riforma Fornero", has among its main goals the reduction of unfair temporary employment relationships.

of the regulation was justified by the idea that temporary jobs may represent a first step towards more stable occupations.

At the same time temporary employment has often been a source of concern, as it may lead to workers' insecurity: for this reason, subsidies in favour of firms willing either to transform temporary positions in permanent ones or to hire new permanent workers have been introduced, in order to reduce the differential cost between permanent and temporary hirings. Until 2000, these subsidies have been small and targeted to a limited subgroup of workers, located in specific areas of the country (Cipollone and Guelfi, 2003). The 2001 Budget Law introduced a more general incentive scheme in favour of firms hiring workers on permanent basis. In particular, the subsidy was addressed to firms increasing the number of permanent employees above the average employment in the pre-policy period (from October 1999 to September 2000), regardless of their geographical location. The incentive was provided by an extension of the tax credit introduced by the 1998 Budget Law, that was designed only for small and medium firms located in the disadvantaged areas of the country (mostly the South).

We use the policy changes due to the introduction and to the subsequent modifications of the incentive as a source of exogenous variation in our estimatation. The incentive took the form of a tax credit of 413 euros per month for each new permanent worker hired and for each conversion of a temporary contract in a permanent one above the pre-treatment employment level. The duration of the subsidy was from the moment the worker was hired to the end of 2003 and the incentive was limited to workers aged more than 25 who had not been employed on permanent basis in the previous two years. The amount of the tax credit was 207 euros higher for firms located in the so called depressed regions. These areas where identified according to what stated by Law 488/98 and they represented almost 50 per cent of the Italian population. In particular, firms benefiting of the additional 207 euros of tax credit where located in the EU Objective 1 areas (GDP less than 75 per cent of the average EU GDP), in Objective 2 areas (industrial regions with unemployment rate higher than the EU average), or Objective 5b areas (peripheral rural regions).

The incentive, that originally was supposed to end in 2003, was extended up to 2006 by the 2003 Budget Law (289/2002). Firms whose permanent employment had increased compared to the pre-policy period (from August 2001 to July 2002) were entitled of 100 euros per month for each new permanent worker (net of layoffs). The credit amounted to 150 euros for new workers aged more than 45 and to 400 euros for firms located in the depressed areas. Moreover, a global limit of 125 mln per year was set to the funding availability.

Given that individual (worker level) data are not available to us, in our analysis we exploit regional, temporal and intensity variation of the policy as source of exogenous variation for the firm's incentive to hire temporary workers. Through this exogenous variation we identify the effect of the share of temporary workers on patent applications. Operationally, we construct our instrument in two steps. First we set a variable equal to 413 for observations surveyed between 2001 and 2003 and located in regions in the Centre and in the North of the country. For firms located in the South this variable takes the value 620. For years 2004-2006, it equals 100 for firms located in the Centre and in the North, whereas it is equal to 400 for firms in the Southern regions. We set this first step variable to zero in years when the tax credit was not in force. Then, we divide the variable that we have just described by the maximum level of the tax credit (620 euros). The instrument therefore captures the relative generosity of the tax credit. We provide summary statistics on the instrument, both in absolute and relative terms in table 7.

Tab. 7. Descriptive statistics: Benefit

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The relevance of the instrument, the capability of the tax credit to generate some variation in the share of permanent workers, is reasonable on theoretical basis and it is supported by the empirical evidence. The size of the tax credit was remarkable. Considering firms that managed to exploit the original subsidy in its entire extension (from the beginning of October 2000 to the end of 2003), the total incentive amounted to almost 16 thousands euros per new permanent worker (26 thousands in the South)[4].

Cipollone and Guelfi (2003) reports descriptive evidence about the use and the effectiveness of this policy in its first year of implementation, arguing that the subsidy was successful in shifting hires towards permanent contracts. Using data provided by the Ministry of Labour (2001), they show that the monthly ratio of foregone revenues (owing to the tax credit) over the overall amount of social security contributions, reached 0.7% in December 2001. In November 2001, the tax credit involved almost 200 thousands workers. Exploiting labour force survey data, Cipollone and Guelfi (2003) also reports that, after having grown since 1993, temporary employment decreased in January 2001, together with the introduction of the tax credit. In 2001, this was associated with a significant increase in permanent employment, the largest since 1993. Nevertheless, compared with the year before, in 2001 the subsidy did not increase the overall probability of being hired.

Hence, the tax credit caused an increase in permanent employment, reducing the share of temporary workers in the recipient firms. But we can also expect the tax credit to have indirect effects on other firms' choices. For instance, the labour cost reduction due to the subsidy may generate windfall profits and it may also change the demand of inputs other than labour. In particular, the subsidy may cause an increase of the investments of credit constrained firms. While in our data we can not control for profits, we evaluate the effect

[4]The subsidy - in its original version - generated a reduction of roughly the 15 per cent of the labour cost in the North and Centre of the country (30 per cent in the South).

of flexible work conditioning on investment and R&D investment. This allows us to take into account changes in capital accumulation associated with the variation of the instrument, which represents a possible threat to its exogeneity.

5 Identification

5.1 Extensive margin

We are interested on estimating the impact of flexibility on two dimensions. The first one focuses on the role of firm's characteristics and its choices on the yearly probability of carrying on at least one successful innovation. The second one looks at how the number of successful projects depends on firm's characteristics and choices. We define the first dimension extensive margin, whereas the second one is called intensive margin.

Concerning the former, the basic idea is that the probability of submitting at least one patent application in a given year, interpreted as the probability of carrying successful innovation, conditional on firm's characteristics, such as its size and industry, depends on the quality and on the quantity of inputs. We are in particular interested in estimating the marginal effect of the composition of the workforce between temporary and permanent workers on the yearly probability of submitting a patent application.

We represent with y_{it} this probability, given the vector X of firm's characteristics:

$$y_{it} = Pr(y_{it} = 1|X),\ i = 1, ..., N;\ t = 1, ..., T$$

We assume that firm's characteristics affect the probability to innovate in a linear manner. Therefore we estimate the following model:

$$y_{it} = \alpha + \delta x_{1it} + x'_{2it}\beta + \gamma_t + \epsilon_{it}, \quad i = 1, ..., N;\ t = 1, ..., T \tag{1}$$

where α and γ_t respectively are a constant and a time fixed effect and x_{2it} is the vector of time variant and invariant characteristics of the firm. The dependent variable y_{it} is a binary variable indicating whether firm i submitted at least one successful patent application in the considered year t. The parameter of interest is δ, which represents the marginal effect of labour flexibility, measured as the percentage of temporary employees over total firm's workforce.

The choice of controls included in the vector x_{2it} comes from earlier theoretical and empirical studies on the determinants of innovation. In particular, we follow the summary that Bugamelli et al. (2012) develops for the Italian case. First of all, we include the annual turnover as a measure for firm size to account for the lower propensity to innovate of small firms. Small firms are in fact usually less innovative since they more likely lack of financial resources, expertise, and opportunity to diversify among risky R&D projects (Zhou et al., 2011). We also control for the amount of sales to foreign customers, since there is strong evidence that international competition increases firm's incentives to innovate. We include R&D expenditure as a proxy for the resources that firms directly allocate to the innovative activity. Moreover, as innovation may indirectly spur from investment other than R&D expenditure, we also include in our model the amount of investments in physical capital. Our specification also includes industry fixed effects (food, textile, chemical, mineral and mechanical industries, other manufactures and other industries), year fixed effects and a geographical dummy capturing the heterogeneity between firms located in the North and those located in the South. Among the main factors affecting innovation that have been analyzed in Bugamelli et al. (2012) we lack of direct controls for the quality of management and of the workforce. For the latter, we estimated the model also taking into account information on average wages for blue and white collars. This information is however missing for a non random fraction of firms. We therefore decided not to include it in our final model, also because other than for reduced precision the main results did not change.

We estimate model 1 first by ordinary least squares. However, the choice of the share of temporary workers by the firm is highly endogenous and it is likely correlated to other unobservable characteristics, which also affect the firm's innovative ability. Therefore, to deal with endogeneity we exploit the policy change described above and we estimate model 1 by two stage least squares. We interpret the policy as an exogenous shock affecting the relative cost of temporary and permanent workers. The residual variation after the first stage allows to identify the causal effect of the share of temporary workers. We also estimate versions of the model where possibly endogenous variables (other than our measure of flexibility) have been omitted using both OLS and 2SLS. In both cases, the presence of controls that may also be endogenous is a problem only when the conditional independence assumption is violated (Stock, 2010).

In all our estimates standard errors are clustered at firm level. This means that we account for the loss of information that is due to the fact that the error terms for the same firm in different years are correlated. Moreover, this structure of the standard errors makes our estimates robust to serial correlation. This is particularly relevant since our estimates come from pooled cross-sections and we include year fixed effects in our model. Finally, we also propose an alternative specification of the model, where the linear probability model is replaced by a logit.

5.2 Intensive margin

The second model we estimate concerns with the effect of temporary workers on the number of patent applications. The extensive margin analysis in fact does not allow to capture whether a lower amount and a lower quality of input decrease the innovation intensity for innovative firms, namely firms that usually patent more than once per year.

We therefore estimate the following model:

$$y_{it} = \alpha + \delta x_{1it} + x'_{2it}\beta + \gamma_t + \epsilon_{it}, \quad i = 1, ..., N;\ t = 1, ..., T \tag{2}$$

where the only difference with model 1 is that y_{it} now represents the number of patent applications in a given year, rather than the probability of submitting at least one patent application in that year. The parameter of interest remains δ, which again captures the marginal effect of the share of temporary workers on the dependent variable.

Some issues related to the empirical distribution of the dependent variable arise when estimating model 2. These are due to the fact that the number of patent applications is a count data. An appropriate regression settings that accommodates for this feature of the dependent variable would increase the efficiency of our estimates. As standard when the dependent variable is count, we estimate a Poisson regression. The robustness of this model to mispecification is similar to OLS in the linear regression under normality. In particular, if the conditional mean is correctly specified, the Poisson estimator is consistent also when the dependent variable is not Poisson: this may well be the case in our data, because of the large fraction of zeros in the dependent variable. Inference, however, requires more care. If the equidispersion assumption does not hold, that is, if the conditional mean differs from the conditional variance, standard errors are incorrect. This is the case in our data, that appears to be overdispersed. Overdispersion determines inflated (deflated) t-tests (standard error) and may result in wrongly attributing significance to some of the covariates. To solve this problem, we base inference on Eicker-White robust covariance estimator. Simulations (Santos Silva and Tenreyro, 2006; 2011) have shown that the Poisson estimator with robust standard errors performs very well in the presence of overdispersion and also with an extremely high share of zeros.

6 Results

Main Results

Table 8 reports OLS estimates of the effect of temporary employment on the yearly probability of applying for at least one patent. The first column refers to a very simple specification, where we included, together with our variable of interest and a constant, a geographical dummy and a set of sector and year dummies. This specification omits relevant variables capturing the characteristics of the firm, but has the advantage of including only variables that are in all probability exogenous. In the following specification (column 2) we add a measure for firm size (turnover). In the third specification (column 3) we also include the other time variant firm observables (export, investment, R&D expenditure) and a dummy indicating the form of the company (limited company or cooperative). This last specification is what we call “the full model”. Column 4 reports the logit estimates of the full model. In all the proposed specifications the coefficient associated with the variable of interest is not statistically significant and its magnitude is small. Control variables have the expected sign: firms in the mechanical and chemical industry submit more patent applications than firms in other sectors. Firms located in the South are less likely to apply for a patent, as the descriptive analysis already pointed out. In model 2 (column 2), turnover is positively correlated with the probability of applying, as one would expect. On the contrary, its coefficient becomes negative when export, investment and R&D expenditure are included. This is due to the fact that these three variables, in particular export, are highly correlated with turnover and, being expressed in levels, also contribute to control for the firm size. Both in the full linear model and in the logit one[5], these three variables are positively correlated with the yearly probability of applying for a patent. The effect is relatively bigger for the variable indicating expenditure in R&D.

OLS estimates are however likely biased, since they suffer from reverse causation and omitted variables. In particular, as discussed in previous sections, the propensity to innovate may affect the workforce composition. To solve this issue we adopt an IV strategy. We identify the effect of temporary employment on the yearly probability to apply for a patent by using the described tax credit as a source of exogenous variation in a 2SLS procedure. Table 9 reports the 2SLS estimates for three different specifications as before. The first one is the basic specification (column 1), the second specification includes turnover as a control for firms size (column 2) and the third one shows the estimated coefficients for the full model (column 3). In this model, by controlling for investment and R&D investment, we account for the effect the policy may have on the dependent variable through changes in capital accumulation. Overall, our 2SLS estimates display a highly significant negative effect of temporary employment on the probability to submit at least one patent application. Results are very stable across specifications but not large: they indicate that a 10 percentage point reduction in the share of temporary workers increases the probability of applying by 0.2 percentage point. In other words, this means that a 10 percentage point reduction in the share of temporary workers corresponds to a 4 per cent increase in the unconditional mean of the yearly probability to apply for a patent.

The relevance of the instrument can be assessed by looking at the first stage estimates in table 10. Conditional on the other covariates, the instrument is significantly correlated with the instrumented variable. Temporary employment tends to be less widespread in the North, in bigger firms and in limited companies.

We next move to the analysis of the effect of temporary employment on the intensive margin, namely on the expected yearly number of patent applications, by estimating model 2. Table 11 reports the OLS estimates. As before, the first column displays the results when only industry and year dummies are included. The second column refers to a specification where turnover is included to control for the firm size. The third column shows the OLS estimates

[5]In order to achieve convergence in the logit specification 14 observations with anomalous level of R&D investment have been deleted form the sample.

of the full model. In column 4 we also report Poisson regression results of the full model. As for the estimation of the effect on the extensive margin, all OLS specifications display no significant association between the share of temporary workers and the number of yearly patent applications. The estimate of the parameter of interest in the Poisson specification (robust to overdispersion) is also not significant.

As discussed for the extensive margin, the OLS estimates are likely affected by the endogeneity of the variable of interest. In table 12 we show 2SLS estimates for the intensive margin, for the three previously outlined specifications, using the same instrument provided by the policy change. The relation between the share of temporary workers and the expected number of patents applications is now negative and statistically significant: a one percentage point increase in temporary employment reduces the expected number of patents applications by roughly 0.1. The results turn out to be stable across specifications.

Overall our evidence suggests that in Italy an increase in labour flexibility tends to dampen innovation measured by the number of patent applications. This result is in contrast with the evidence about Spain (Martinez-Sanchez et al, 2009), where more flexibility is associated with more innovation but consistent with what was found for other countries (Zhou et al (2011), for Netherlands).

In the last 15 years the cost of temporary workers in Italy has decreased a lot faster than in other main economies, while their protection has decreased, being now lower than in most European countries. To support the idea of high relative cost of permanent workers relative to temporary ones, we can use OECD data on employment protection legislation. OECD provides information on the protection of permanent workers in terms of firing cost and it provides a measure of how tight the regulation of temporary contracts is. Using the ratio between the indices summarizing the protection of temporary and permanent workers we have a measure of the relative cost of temporary workers (figure 1). By making temporary employment less costly, these reforms may have reduced the demand for skilled permanent workers in favour of that for temporary workers, contributing to the specialization of the country in scarcely innovative productions. However, given that workers level data are not available to us, in our research we are not able to assess whether low innovation is due to the lower level of general and firm specific human capital of temporary workers or to lower incentives to contribute to the innovative activity.

Differential effects across industries

So far we have imposed a restriction on our estimates, assuming that the average conditional effect of the share of temporary workers on firm's innovation is constant across industries. However this relation is likely different in its intensity between high-tech industries, often innovation oriented, and in other industries, that usually are less innovative and show a lower propensity to patent their discoveries. We estimate the effect of labour flexibility on innovation for firms operating in high-tech and low-tech industries separately, exploiting the industry classification provided by Eurostat by degree of technological intensity. The first estimate focuses on high-tech firms, namely those operating in the following Ateco91 classes: DG24 and DK29 to DM35. This means that firms are considered high-tech when they operate in chemical, machinery, computer and electronic product, or transportation equipment industry. The second estimates is on the sample of remaining firms, that for convenience are here called low-tech.

In our sample, the average number of patent applications among high-tech firms is about 0.5, whereas for the low-tech firms the average number of applications is lower than 0.1. The average yearly probability of applying for at least one application is 11.4 per cent for high-tech firms, whereas it is only 2.7 per cent for the low-tech.

We first focus on the extensive margin, estimating model 1 separately for the two groups of firms. Column 1 and 3 of table 13 report the OLS estimated coefficients for high-tech and low tech firms. The estimates of δ are statistically insignificant and of a small magnitude for both groups. However, issues of endogeneity similar to those discussed in the earlier sections emerge, and the unobservable characteristics leading to biased estimates of δ are presumably different between high and low-tech firms, making the interpretation of OLS estimates even more complex.

Therefore, in order to get causal relationship, we estimate two separate 2SLS models, adopting again the policy change as the source for exogenous variation. Column 2 and 4 of table 13 report IV estimates for high and low tech firms. It emerges that the negative effect of temporary employment on the yearly probability to innovate is statistically significant and of an economically relevant magnitude only for high-tech firms. There is, on the other hand, no evidence of a significant effect for low-tech firms.

Adopting the same strategy, we estimate the effect of labour flexibility on the intensive margin. Table 14 shows the estimated OLS and 2sls coefficients for high and low-tech firms. As before, OLS estimates display no relation between the share of temporary workers and the yearly number of patent applications. However, 2SLS estimates show a negative and significant effect for high-tech firms, whereas there is no effects on the innovation of low-tech firms.

The interpretation of this evidence is not straightforward. The fact that a higher demand of temporary workers reduce innovation only among high-tech firms may reflect the wider skills gap between permanent and temporary workers in these firms. In low-tech firms, labour is on average less skilled and the skills gap between temporary and permanent workers is narrower. It is important to bear in mind that our data do not allow us at all to control for workers' skills or for their education. Additionally, an increase in flexibility may result in a larger reduction of innovation among high-tech firms because in these firms a higher fraction of the workforce is devoted to the innovative activity. This means that in low-tech firms, the same increase in the share of temporary workers would produce smaller effects since it is spread across workers that are not involved in the production of innovation.

7 Conclusion

In this paper we investigate how innovation is affected by the degree of labour flexibility at the firm level. Labour flexibility is measured by the proportion of temporary workers employed by a firm. We use information on patent applications provided by the European Patent Office as our measure of innovation. Exploiting information on the applicant's identifier, we link patent applications to the representative sample of industrial firms in the Bank of Italy's survey of industrial and service firms (Invind). We study the effect of the proportion of temporary workers on the yearly probability of submitting at least one patent application (extensive margin) and on the yearly number of patent applications submitted (intensive margin).

Our results show that, after dealing with the endogeneity of OLS estimates, a higher proportion of temporary workers reduces the ability of a firm to produce innovation. We deal with the endogeneity of our variable of interest, the proportion of temporary workers, by exploiting a policy change that modified the relative cost of temporary and permanent workers. Changes in the relative cost of the two types of labour due to the policy provide a reasonable source for exogenous variation of the demand for temporary and permanent workers.

In particular, our results indicate that a higher proportion of temporary workers reduces the yearly probability of submitting a patent application. This effect is not large but is statistically significant. Our estimates also show that an increase in labour flexibility reduces the yearly number of patents. Given that worker level data are not available to us, we are unable to assess whether the negative relationship is because temporary workers have a low general of firm specific endowment of human capital or because temporary contracts have a negative effect on workers' incentives to innovate.

We also test whether the effect of labour flexibility is the same for firms operating in high and low-tech industries. Our results imply that a higher proportion of temporary workers, reduces innovation considerably among high-tech firms, whereas no significant effect is found among the other firms.

This evidence suggests that firms may be willing to trade innovation and future profit against lower current labour cost, shedding some light on another possible channel explaining the innovative gap affecting Italian firms. The labour market reforms passed in Italy since the end of the 1990s have widened the gap between the cost of permanent and temporary workers. This may have contributed, together with other well-known structural weaknesses of the Italian economy, to the low level of innovation and to the slow growth experienced in the last decade.

Bibliography

Addessi, W., E. Saltari and R. Tilli, The R&D and Innovation Activities and the Use of External Numerical Flexibility, *mimeo*.

Bassanini, A. and E. Ernst, 2002, Labour Market Institutions, Product Market Regulation, and Innovation, *OECD Working Papers 316*.Beatson, M., 1995, Labour Market Flexibility, *Research Series 48*, Sheffield, Employment Department.

Becker, S. O. and Egger, P. H., 2007, Employment Effects of Product and Process Innovation, *mimeo*.

Bentolila, S. and J. Dolado, 1994, Labour Flexibility and Wages: Lessons from Spain", *Economic Policy,* 18.

Bugamelli, M., L. Cannari, F. Lotti and S. Magri, 2012, Il gap innovativo del sistema produttivo italiano: radici e possibili rimedi, *Bank of Italy Occasional Papers,* 121.

Cipollone, P. and A. Guelfi, 2003, Tax Credit Policy and Firms' Behaviour: The Case of Subsidy to Open-End Labour Contract in Italy," Economic Working Papers, Bank of Italy.

Cameron, C. and P. K. Trivedi, 1998, Regression Analysis of Count Data, Econometric Society Monographs.

Crepon, B., E. Duguet and J. Mairesse, 1998, Research, Innovation and Productivity: An Econometric Analysis at the Firm Level, *NBER Working Paper,* 6696.

Griffith, R., E. Huergo, J. Mairesse and B. Peters, 2006, Innovation and Productivity across four European Countries, *Oxford Review of Economic Policy,* 22(4).

Jackman, R., R. Layard, and S. Nickell, 1996, Combating Unemployment: Is Flexibility Enough?, *CEP Working Paper*.

Jacob, B. A., 2010, The Effect of Employment Protection on Worker Effort: Evidence from Public Schooling, *NBER Working Paper*.

Hall, B. H.; A. B. Jaffe and M. Trajtenberg, 2001, The NBER Patent Citation Data File: Lessons, Insight and Methodological Tools, *NBER Working Papers*.

Hopenhayn, H. and R. Rogerson, 1993, Job Turnover and Policy Evaluation: A General Equilibrium Analysis, *The Journal of Political Economy,* 101(5).

Ichino, A and R. T. Riphahan, 2005, The Effect of Employment Protection on Worker Effort: A Comparison of Absenteeism During and After Probation, *Journal of the European Economic Association,* 3(1).

Istat, 2012a, I flussi occupazionali in entrata e in uscita nelle grandi imprese per tipologia di contratto.

Istat, 2012b, Rapporto Annuale 2012: La situazione del Paese.

Lotti, F. and E. Viviano, 2012, Temporary Workers, Uncertainty and Productivity, *mimeo*.

Malcomson, J. M., 1997, Contracts, hold-up, and labor markets, *Journal of Economic Literature,* 19.

Malgarini, M., M. Mancini and L. Pacelli, 2012: Temporary hires and innovative investments, *Applied Economics*, 45.

Marin, G., 2012, Matching of Patstat to AIDA firms. Discussion of the Methodology and Results, *mimeo*Saint-Paul, G., 2002, Some Thoughts on Macroeconomic Fluctuations and the Timing of Labor Market Reform, *IZA Discussion Papers 611.*

Martinez-Sanchez, 2009: *Innovation and Labour Flexibility, International Journal of Manpower, 30(4).*

Ministero del Lavoro e delle Politiche Sociali, 2001, Rapporto di Monitoraggio sulle Politiche Occupazionali e del Lavoro, No. 2.

OECD, 2012, Employment Outlook, *http://stats.oecd.org/Index.aspx?DataSetCode=TEMP_I.*

Samaniego, 2006, Employment Protection and high-tech aversion, *Review of Economic Dynamics*, 9(2).

Santos Silva, J. and S. Tenreyro, The Log of Gravity, *The Review of Economics and Statistics*, 88(4).

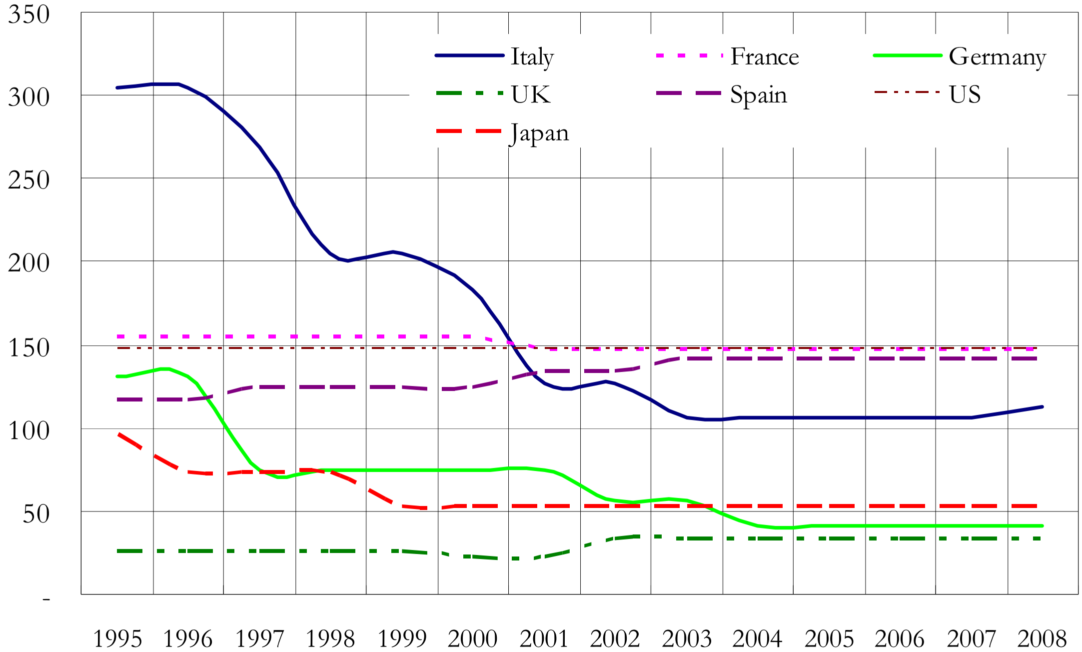
Santos Silva, J. and S. Tenreyro, 2011, Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum likelihood Estimator, *Economic Letters*, 112(4)

Stock, J., 2010, The Other Transformation in Econometric Practice: Robust Tools for Inference, *Journal of Economic Perspectives*, 24(2)

Zhou, H., R. Dekker and A. Kleinknecht, 2011, Flexible Labour and Innovation Performance: Evidence from Longitudinal Firm-Level Data, *Industrial and Corporate Change*, 10.

Contents

Fig. 1. Ratio of temporary on permanent worker protection indeces



Source: OECD (2012)

Tab.1. Patent applications and shares by year and area in the matched data set

Priority year	North West		North East		Centre		South		Italy
2001	301	*43.5*	187	*27.0*	190	*27.5*	14	*2.0*	692
2002	441	*50.4*	172	*19.7*	252	*28.8*	10	*1.1*	875
2003	400	*45.9*	220	*25.2*	229	*26.3*	23	*2.6*	872
2004	482	*52.6*	172	*18.8*	243	*26.5*	19	*2.1*	916
2005	563	*48.2*	302	*25.9*	259	*22.2*	44	*3.8*	1 168
2006	550	*53.2*	281	*27.2*	184	*17.8*	18	*1.7*	1 033
2007	456	*50.2*	213	*23.5*	205	*22.6*	34	*3.7*	908
2008	352	*49.6*	176	*24.8*	160	*22.6*	21	*3.0*	709
Total	3 729	*49.6*	1 808	*24.0*	1 780	*23.7*	205	*2.7*	7 522
2009	181	*52.6*	84	*24.4*	57	*16.6*	22	*6.4*	344
2010	3	*60.0*	1	*20.0*	1	*20.0*	0	*0.0*	5

Note: shares in italics.

Tab. 2. Patent applications and shares by year and area in Patstat

Priority year	North West		North East		Centre		South		Italy
2001	1 545	*47.07*	1 138	*34.67*	488	*14.87*	111	*3.38*	3 282
2002	1 807	*50.74*	1 127	*31.65*	524	*14.71*	103	*2.89*	3 561
2003	1 782	*49.62*	1 195	*33.28*	487	*13.56*	127	*3.54*	3 591
2004	1 808	*48.50*	1 219	*32.70*	565	*15.16*	136	*3.65*	3 728
2005	1 785	*46.45*	1 369	*35.62*	542	*14.10*	147	*3.83*	3 843
2006	1 798	*46.65*	1 446	*37.52*	439	*11.39*	171	*4.44*	3 854
2007	1 655	*44.16*	1 402	*37.41*	521	*13.90*	170	*4.54*	3 748
2008	1 280	*43.90*	1 108	*38.00*	412	*14.13*	116	*3.98*	2 916
Total	14 151	*47.06*	10 623	*35.33*	4 135	*13.75*	1 163	*3.87*	30 072
2009	671	*44.41*	605	*40.04*	155	*10.26*	80	*5.29*	1 511
2010	20	*52.63*	14	*36.84*	2	*5.26*	2	*5.26*	38

Note: shares in italics.

Tab. 3.Coverage shares in the matched data set

Priority year	North West	North East	Centre	South	Italy
2001	19.5	16.4	38.9	12.6	21.1
2002	24.4	15.3	48.1	9.7	24.6
2003	22.4	18.4	47.0	18.1	24.3
2004	26.7	14.1	43.0	14.0	24.6
2005	31.5	22.1	47.8	29.9	30.4
2006	30.6	19.4	41.9	10.5	26.8
2007	27.6	15.2	39.3	20.0	24.2
2008	27.5	15.9	38.8	18.1	24.3
Total	26.4	17.0	43.0	17.6	25.0
2009	27.0	13.9	36.8	27.5	22.8
2010	15.0	7.1	50.0	0.0	13.2

Tab. 4. Innovative and not innovative firms by sector and area

Sector	Not Innov.	(%)	Innov.	(%)	Total
# Observations by sector					
Food	1165	98.8	14	1.2	1179
Textile	2306	98.5	35	1.5	2342
Chemical	1768	92.6	142	7.4	1910
Minerals	844	97.7	20	2.3	865
Mechanical	6893	91.5	644	8.5	7537
Other manif.	2080	97.8	46	2.2	2126
Others	541	99.6	2	0.4	543
# Observations by area					
North West	6497	94.2	402	5.8	6900
North East	4941	93.0	372	7.0	5313
Centre	2329	95.6	107	4.4	2436
South	1831	98.9	21	1.1	1852
Total	15598	94.5	903	5.5	16501
# Firms by sector					
Food	267	98.3	5	1.7	271
Textile	568	96.4	21	3.6	589
Chemical	390	85.9	64	14.1	454
Minerals	198	93.1	15	6.9	212
Mechanical	1466	84.1	277	15.9	1743
Other manif.	507	94.3	31	5.7	538
Others	142	98.9	2	1.1	143
# Firms by area					
North West	1366	87.5	196	12.5	1562
North East	1147	88.3	153	11.7	1300
Centre	523	91.7	47	8.3	571
South	470	97.0	15	3.0	485
Total	3537	89.5	414	10.5	3951

Tab. 5. Descriptive Statistics: Patent applications per year, area and sector

Variable	Mean	Std. Err.	95% Conf. Interval	
# of Patents per year				
Not innovative	0			
Innovative	3.74	0.17	3.40	4.07
# of Patents by area				
North West	0.23	0.02	0.19	0.27
North East	0.23	0.02	0.20	0.27
Centre	0.20	0.02	0.17	0.24
South	0.02	0.004	0.02	0.03
# of Patents by area (only innovative firms)				
North West	3.96	0.32	3.33	4.59
North East	3.33	0.19	2.95	3.70
Centre	4.62	0.42	3.79	5.45
South	2.14	0.29	1.57	2.71
# of Patents by year				
2001	0.14	0.03	0.09	0.19
2002	0.20	0.03	0.13	0.26
2003	0.18	0.03	0.13	0.23
2004	0.19	0.03	0.13	0.25
2005	0.26	0.04	0.19	0.33
2006	0.31	0.04	0.22	0.39
2007	0.27	0.04	0.19	0.34
2008	0.21	0.03	0.16	0.26
2009	0.09	0.01	0.06	0.12
# of Patents by sector				
Food	0.04	0.01	0.02	0.06
Textile	0.04	0.01	0.02	0.07
Chemical	0.30	0.03	0.25	0.36
Minerals	0.05	0.02	0.02	0.09
Mechanical	0.33	0.02	0.28	0.37
Other manif.	0.05	0.01	0.03	0.07
Others	0.06	0.02	0.01	0.10
Total	0.20	0.01	0.18	0.23

Tab. 6. Descriptive Statistics: Covariates

Variable	Mean	Std. Err.	95% Conf. Interval	
Share of temporary workers				
Not innovative	6.10	0.11	5.88	6.32
Innovative	5.37	0.31	4.76	5.99
All	6.06	0.11	5.85	6.27
Turnover (1)				
Not innovative	58.45	1.98	54.56	62.34
Innovative	208.70	21.62	166.32	251.08
All	66.69	2.21	62.36	71.01
Export (1)				
Not innovative	1.66	0.04	1.58	1.74
Innovative	9.41	0.79	7.86	10.96
All	2.08	0.06	1.97	2.19
Investment in physical capital (1)				
Not innovative	0.24	0.01	0.22	0.26
Innovative	0.67	0.06	0.55	0.78
All	0.26	0.01	0.24	0.29
R&D investment (1)				
Not innovative	0.02	0.00	0.02	0.03
Innovative	0.33	0.04	0.26	0.40
All	0.04	0.00	0.04	0.05
# Temporary workers				
Not innovative	9.36	0.19	8.98	9.74
Innovative	25.02	1.79	21.50	28.53
All	10.22	0.21	9.81	10.62
# Employed workers				
Not innovative	166.30	2.39	161.62	170.98
Innovative	515.69	23.31	469.99	561.39
All	185.46	2.56	180.44	190.47
Share of limited companies				
Not innovative	0.99	0.00	0.98	0.99
Innovative	0.99	0.00	0.99	1.00
All	0.99	0.00	0.98	0.99

Note: (1) units in mln of euros.

Tab. 7. Descriptive Statistics: Benefit

Variable		Mean	Std. Err.	95% Conf. Interval	
Average benefit					
Not Innovative	*North West*	142	3.1	136	148
	North East	137	3.5	130	144
	Centre	137	3.3	131	144
	South	315	4.6	306	324
	Italy	160	1.9	156	164
Innovative	*North West*	119	9.3	101	137
	North East	111	8.4	95	128
	Centre	133	11.7	110	156
	South	301	37.1	228	374
	Italy	122	5.7	110	133
Total	*North West*	140	3.0	135	146
	North East	135	3.3	129	141
	Centre	137	3.2	131	143
	South	315	4.5	306	324
	Italy	158	1.8	154	161
Average benefit/Max benefit					
Not Innovative	*North West*	0.23	0.005	0.22	0.24
	North East	0.22	0.006	0.21	0.23
	Centre	0.22	0.005	0.21	0.23
	South	0.51	0.007	0.49	0.52
	Italy	0.26	0.003	0.25	0.26
Innovative	*North West*	0.19	0.015	0.16	0.22
	North East	0.18	0.014	0.15	0.21
	Centre	0.21	0.019	0.18	0.25
	South	0.49	0.060	0.37	0.60
	Italy	0.20	0.009	0.18	0.21
Total	*North West*	0.23	0.005	0.22	0.24
	North East	0.22	0.005	0.21	0.23
	Centre	0.22	0.005	0.21	0.23
	South	0.51	0.007	0.49	0.52
	Italy	0.25	0.003	0.25	0.26

Tab. 8. Extensive Margin

	(1) OLS	(2) OLS	(3) OLS	(4) Logit
Dependent Variable: Has applied for a patent in the year				
Share temp. Work.	-0.00013	-0.00011	-0.00011	-0.0020
	(-0.81)	(-0.69)	(-0.66)	(-0.43)
Nord	0.025	0.025	0.024	0.60
	(4.48)***	(4.47)***	(4.29)***	(4.06)***
Industry Dummies (ref: Food Ind.)				
Textile	0.0048	0.0062	0.0040	0.26
	(0.77)	(1.01)	(0.61)	(0.55)
Chemical	0.060	0.059	0.058	1.76
	(5.57)***	(5.50)***	(5.29)***	(4.21)***
Minerals	0.016	0.017	0.015	0.79
	(1.86)*	(2.01)**	(1.80)*	(1.61)
Mechanical	0.072	0.073	0.069	1.96
	(8.80)***	(8.96)***	(8.24)***	(4.90)***
Other manifactures	0.011	0.012	0.010	0.62
	(1.62)	(1.82)*	(1.50)	(1.38)
Others	-0.0037	-0.0099	-0.0054	-1.73
	(-0.67)	(-1.86)*	(-0.95)	(-2.52)**
Turnover		0.0025	-0.0021	-0.012
		(2.94)***	(-2.83)***	(-1.13)
Export			0.17	2.65
			(3.75)***	(3.83)***
Investment			0.20	1.34
			(2.64)***	(0.54)
R&D Expen.			1.38	39.6
			(1.30)	(2.77)***
Limited Company			0.0012	0.17
			(0.09)	(0.26)
Year dummies	X	X	X	X
Constant	-0.027	-0.029	-0.028	-5.44
	(-3.12)***	(-3.35)***	(-2.48)**	(-9.87)***
Number of Obs.	16501	16501	16442	16428

Note: T-statistics in parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab. 9. Extensive Margin: IV

	(5) 2SLS	(6) 2SLS	(7) 2SLS
Dependent Variable: Has applied for a patent in the year			
Share temp. Work.	-0.018	-0.018	-0.017
	(-2.65)***	(-2.61)***	(-2.72)***
Nord	-0.031	-0.030	-0.027
	(-1.35)	(-1.29)	(-1.31)
Industry Dummies (ref: Food Ind.)			
Textile	-0.088	-0.084	-0.071
	(-2.19)**	(-2.13)**	(-2.15)**
Chemical	-0.033	-0.031	-0.018
	(-0.80)	(-0.76)	(-0.51)
Minerals	-0.077	-0.073	-0.061
	(-1.91)*	(-1.85)*	(-1.81)*
Mechanical	-0.0073	-0.0042	0.0059
	(-0.21)	(-0.12)	(0.20)
Other manifactures	-0.084	-0.080	-0.068
	(-2.05)**	(-1.99)**	(-1.98)**
Others	-0.11	-0.11	-0.095
	(-2.41)**	(-2.52)**	(-2.45)**
Turnover		0.0020	-0.0025
		(2.46)**	(-3.06)***
Export			0.17
			(3.84)***
Investment			0.20
			(2.49)**
R&D Expen.			1.36
			(1.32)
Limited Company			-0.070
			(-1.52)
Year dummies	X	X	X
Constant	0.20	0.19	0.15
	(2.26)**	(2.20)**	(2.13)**
Number of Obs.	16501	16501	16442

Note: T-statistics in parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab 10: First Stage IV

	(15) OLS	(16) OLS	(17) OLS
Dependent Variable: Share temp. Work.			
Instrument	3.78	3.75	3.92
	(3.02)***	(3.00)***	(3.17)***
Nord	-2.64	-2.64	-2.52
	(-7.29)***	(-7.30)***	(-7.06)***
Industry Dummies (ref: Food Ind.)			
Textile	-5.01	-5.03	-4.32
	(-5.21)***	(-5.23)***	(-4.58)***
Chemical	-5.09	-5.07	-4.38
	(-5.29)***	(-5.28)***	(-4.64)***
Minerals	-5.04	-5.06	-4.43
	(-4.83)***	(-4.84)***	(-4.33)***
Mechanical	-4.35	-4.36	-3.67
	(-4.71)***	(-4.72)***	(-4.06)***
Other manifactures	-5.17	-5.18	-4.51
	(-5.10)***	(-5.11)***	(-4.55)***
Others	-5.89	-5.82	-5.19
	(-5.12)***	(-5.05)***	(-4.50)***
Turnover		-0.028	-0.023
		(-3.73)***	(-1.95)*
Export			-0.22
			(-0.52)
Investment			0.088
			(0.07)
R&D Expen.			-1.11
			(-0.21)
Limited Company			-4.24
			(-2.09)**
Year dummies	X	X	X
Constant	12.0	12.0	9.79
	(12.15)***	(12.16)***	(7.86)***
Number of Obs.	16501	16501	16442

Note: T-statistics in parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab. 11. Intensive Margin

	(8) OLS	(9) OLS	(10) OLS	(11) Poisson
Dependent Variable: Number of patent applications in the year				
Share temp. Work.	-0.0010 (-1.36)	-0.00064 (-0.82)	-0.00065 (-0.82)	-0.012 (-1.56)
Nord	0.068 (1.70)*	0.066 (1.67)*	0.043 (1.23)	0.37 (1.53)
Industry Dummies (ref: Food Ind.)				
Textile	-0.0030 (-0.11)	0.026 (0.92)	0.0044 (0.10)	0.18 (0.25)
Chemical	0.25 (3.70)***	0.23 (3.37)***	0.24 (3.30)***	2.10 (3.23)***
Minerals	0.016 (0.51)	0.040 (1.27)	0.023 (0.52)	0.40 (0.57)
Mechanical	0.28 (5.13)***	0.29 (5.30)***	0.23 (4.43)***	2.06 (3.27)***
Other manifactures	0.0059 (0.23)	0.032 (1.17)	0.022 (0.55)	0.36 (0.55)
Others	0.039 (0.66)	-0.089 (-2.40)**	-0.023 (-0.29)	-0.48 (-0.38)
Turnover		0.052 (2.60)***	-0.086 (-1.04)	-0.089 (-1.44)
Export			4.25 (2.04)**	2.34 (1.72)*
Investment			11.2 (1.00)	6.79 (1.99)**
R&D Expen.			27.3 (1.13)	1.02 (0.06)
Limited Company			-0.22 (-0.85)	-1.41 (-1.51)
Year dummies	X	X	X	X
Constant	-0.12 (-2.53)**	-0.16 (-3.08)***	-0.23 (-1.81)*	-4.84 (-5.30)***
Number of Obs.	16501	16501	16442	16428

Note: T-statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab. 12. Intensive Margin: IV

	(12) 2SLS	(13) 2SLS	(14) 2SLS
Dependent Variable: Number of patent applications in the year			
Share temp. Work.	-0.11	-0.094	-0.092
	(-2.50)**	(-2.40)**	(-2.51)**
Nord	-0.26	-0.22	-0.23
	(-1.73)*	(-1.58)	(-1.79)*
Industry Dummies (ref: Food Ind.)			
Textile	-0.55	-0.45	-0.40
	(-2.23)**	(-2.03)**	(-2.07)**
Chemical	-0.30	-0.25	-0.17
	(-1.25)	(-1.17)	(-0.89)
Minerals	-0.53	-0.44	-0.39
	(-2.15)**	(-1.96)*	(-1.97)**
Mechanical	-0.19	-0.12	-0.11
	(-0.90)	(-0.60)	(-0.66)
Other manifactures	-0.55	-0.46	-0.40
	(-2.20)**	(-2.01)**	(-2.01)**
Others	-0.60	-0.64	-0.51
	(-2.09)**	(-2.45)**	(-2.10)**
Turnover		0.049	-0.088
		(2.49)**	(-1.07)
Export			4.23
			(2.04)**
Investment			11.2
			(1.00)
R&D Expen.			27.2
			(1.13)
Limited Company			-0.60
			(-1.71)*
Year dummies	X	X	X
Constant	1.21	1.00	0.70
	(2.20)**	(2.01)**	(1.67)*
Number of Obs.	16501	16501	16442

Note: T-statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab. 13. Extensive Margin: High Tech (HT) and Low Tech (LT) Firms

	(18) OLS HT	(19) 2SLS HT	(20) OLS LT	(21) 2SLS LT
Dependent Variable: Has applied for a patent in the year				
Share temp. Work.	-0.00022	-0.025	-0.000010	-0.0014
	(-0.44)	(-2.57)**	(-0.11)	(-0.53)
Nord	0.031	-0.057	0.019	0.016
	(2.01)**	(-1.42)	(4.91)***	(1.82)*
Turnover	-0.012	-0.012	-0.00083	-0.00087
	(-1.41)	(-1.39)	(-2.49)**	(-2.50)**
Export	0.43	0.40	0.084	0.085
	(3.03)***	(2.62)***	(3.85)***	(3.84)***
Investment	0.18	0.39	0.083	0.083
	(0.25)	(0.49)	(2.30)**	(2.26)**
R&D Expen.	0.66	0.77	4.12	4.11
	(0.79)	(0.91)	(2.48)**	(2.47)**
Limited Company	-0.056	-0.064	0.014	0.0051
	(-0.40)	(-0.41)	(1.65)*	(0.26)
Year dummies	X	X	X	X
Constant	0.0096	0.20	0.0096	0.017
	(0.19)	(2.17)**	(1.68)*	(1.10)
Number of Obs.	5517	5517	10925	10925

Note: T-statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01
Turnover, Export, Investment and R&D Expenditure in tens of mlns

Tab. 14 Intensive Margin: High Tech (HT) and Low Tech (LT) Firms

	(22) OLS HT	(23) 2SLS HT	(24) OLS LT	(25) 2SLS LT
Dependent Variable: Number of patent applications in the year				
Share temp. Work.	-0.0017 (-0.71)	-0.13 (-2.27)**	0.000038 (0.14)	-0.030 (-1.13)
Nord	0.11 (1.05)	-0.35 (-1.49)	0.029 (1.14)	-0.047 (-0.53)
Turnover	-1.06 (-1.55)	-1.06 (-1.55)	0.0039 (0.67)	0.0030 (0.50)
Export	14.7 (1.93)*	14.5 (1.91)*	1.49 (7.52)***	1.51 (7.43)***
Investment	192.8 (1.37)	193.8 (1.38)	-0.32 (-0.67)	-0.33 (-0.70)
R&D Expen.	-9.50 (-0.39)	-8.92 (-0.37)	50.4 (3.90)***	50.1 (3.87)***
Limited Company	-3.18 (-1.02)	-3.22 (-1.03)	0.036 (1.35)	-0.16 (-0.89)
Year dummies	X	X	X	X
Constant	-1.09 (-1.04)	-0.078 (-0.07)	-0.0069 (-0.29)	0.15 (0.95)
Number of Obs.	5517	5517	10925	10925

Note: T-statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01
Turnover, Export, Investment and R&D Expenditure in tens of mlns