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Work arrangements and firm innovation: is there any relationship?

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This study investigates the relationship between labour market flexibility—proxied by the proportion of workers with different contractual arrangements and other indicators of flexible work relations—and firms' innovative ability, as measured by the percentage of new products in total sales. On the one hand, 'more flexibility' (e.g. a higher labour turnover) might be favourable to a firm's innovation potential. Aside from having (potential) wage savings, a larger inflow of new personnel may enrich the pool of firm innovative ideas. On the other hand, higher work flexibility may also have some drawbacks: a permanently high turnover rate may diminish social cohesion and trust and increase the probability of opportunistic behaviour. Results suggest that internal flexibility is positively associated with innovation for both high-tech and low-tech firms. Especially for high-tech firms, however, greater external flexibility might hinder innovation.

Key words: Flexible labour, Innovation, Limited dependent variables
JEL classifications: C34, L60, O31

1. Introduction

Beginning with the seminal paper of Lazear (1990), the majority of studies on labour market institutions have examined the relationship existing between these institutions and unemployment (see Blanchard, 2006, for a review). Although very important, concentrating on this aspect has implied neglect for other, equally relevant elements. There is still little focus in the existing microeconomic literature on the effect of work arrangements on firms' ability to innovate. On the contrary, we claim that labour market institutions may have a significant impact on firm innovativeness. Similarly, virtually all of the economic literature on firm-level determinants of innovation has addressed issues such as corporate size, the degree of competition and the extent of protection granted by patents, thus neglecting organisational factors and human resource management practices that may provide a positive contribution to firm innovation performance (see Mairesse and Mohnen, 2010, for a review).

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As a first attempt to fill this gap, we propose an empirical investigation aimed at examining the effect of work arrangements on firms' ability to invest and introduce new technologies. In particular, this study relies on a panel of Italian manufacturing firms to investigate the relationship between labour market flexibility—as measured by the share of workers under different work arrangements or who have received training as well as by the share of workers who have left or joined the firm (i.e. labour turnover)—and firms' innovative capacity, as measured by the percentage of new products in corporate total sales. As we want to adopt a firm perspective, the focus will be on flexibility at the firm level (both internal and external), thus ignoring—insofar as possible—other labour market features (i.e. labour mobility across sectors and regions).

The reasoning for distinguishing between different kinds of flexibility relies on the assumptions—as argued in various theoretical papers (see, e.g., MacLeod, 2005)—that their consequences for firm performance might be very different. On the one hand, one might argue that 'more flexibility' (e.g. a higher labour turnover) might be favourable for firms' innovation potential. A larger inflow of new people may enrich the pool of innovative ideas and/or make it easier for a firm to replace less productive people with more productive ones. On the other hand, higher labour flexibility may also have some disadvantages. A permanently high turnover rate may diminish social cohesion and trust and increase the probability of opportunistic behaviour. Long-term and trust-based relations may instead be required to develop tacit organisational competences and skills, which would improve productivity and performance by selecting and allocating competent people. In addition, such flexibility will diminish social capital, thus concurrently forcing firms to invest more money in monitoring and controlling (Naastepad and Storm, 2005), making the so-called 'hold up' problem even more relevant: as labour contracts are expected to be shorter, employer and employees may be reluctant to really invest in labour relations (Kleinknecht *et al.*, 2006). However, we expect the consequences to be very different, depending on firm activities. In fact, the loss of social capital might be a much more serious concern for innovative and knowledge-intensive firms. In such a case, much of the knowledge created by firm activities is embedded, to some extent, in the employees' human capital and, therefore, employees are not simply interchangeable with those outside the firm. In addition, the risk of revealing trade secrets and technological knowledge might discourage firm investments in R&D and innovation. Therefore, throughout our empirical analysis, we will distinguish between results for firms in low-tech and high-tech industries.

We will progressively use the dataset panel structure. Initially, we adopt a cross-sectional Heckman selection model (i.e. Tobit type II) to account for the fact that firms are either innovative or not and, among the innovative firms, to check to what extent they are so (Mohnen *et al.*, 2006). This strategy allows us to address selectivity problems. Secondly, we will rely on a Heckman panel estimator to control for endogeneity problems arising from unobserved firm characteristics. Specifically, we choose to rely on the estimator proposed by Rochina-Barrachina (1999), which extends the cross section Heckman's estimator to two different time periods. Our results suggest that internal flexibility is positively associated with innovation for both types of firms. In high-tech firms the evidence suggests that greater external flexibility—and, in particular, a greater labour turnover—may have negative effects on innovation.

The paper is structured as follows. In the next section we will briefly discuss different types of flexible labour. In Section 3 we will give a review of the literature on studies that either theoretically or empirically attempt to investigate the effect of work arrangements on firm productivity and ability to innovate. Subsequently, after a description in Section 4 of the Italian labour market and dataset used, we present in Section 5 the econometric model and results. The final section contains our comments and conclusions.

2. Labour flexibility: meanings and implications

To outline how different work arrangements might affect firms' performance, in this section we will describe different forms of flexible labour. Labour market flexibility can be divided into three broad categories: *market flexibility*, *external flexibility* and *internal flexibility*.

Market flexibility refers to the flexibility of the whole labour market, i.e. the degree to which wages are adjusted to clear the market (wage flexibility) and the degree to which people move between jobs, occupations, industries and geographical areas (labour mobility). We expect that there are intrinsic differences in work mobility according to different features of skilled job requirements among sectors as well as a different degree of wage flexibility related to the strength of labour organisations. In industries characterised by routine technological change (e.g. due to the specificity of competencies), the loss of a few staff members may involve significant costs, such that the scope for the external labour market is rather limited (Malerba and Orsenigo, 2000).

External flexibility (or numerical flexibility) concerns the numerical change in the number of workers needed to meet firm requirements, and it is achieved when hiring and dismissing employees is relatively easy and temporary contracts are made. These are often called 'low-road' practices, leading to higher staff turnover and (possibly) to low-trust labour relations (Michie and Sheehan-Quinn, 2001; Kleinknecht *et al.*, 2006). *Internal flexibility* is generally identified with functional flexibility, which implies the elimination of horizontal and/or vertical boundaries between job classifications and the development of multiskilled employees. Because changes in skill requirements are achieved mainly through training, internal flexibility does not yield wage cost savings and, on the contrary, might even lead to a significant increase of these costs. To emphasise the qualitative adaptation of worker competences to the company's changing needs, these arrangements are often called 'high-road' practices (Michie and Sheehan-Quinn, 2001; Kleinknecht *et al.*, 2006). However, there is also a notion of *internal numerical (quantitative) flexibility*, sometimes known as working-time flexibility, achieved by adjusting working hours or schedules of workers already employed within the firm. This includes part-time, overtime, flexible working hours, working time accounts, seasonal changes and leave of any kind. Even though the objectives are different from functional flexibility, on the one hand, flexible working time arrangements and leave schemes can be used to accommodate working-hour preferences and enhance loyalty, enabling workers to match care and other responsibilities along with work responsibility as well as training or educational breaks (Houseman, 2001). From this perspective, for example, part-time employment can be thought to reconcile both employee and employer needs (Chung, 2006). On the other hand, working-time flexibility can lead to jobs of poorer quality compared with similar full-time jobs. For example, part-time jobs may be of lesser quality in their terms and conditions of employment: hourly wages, non-wage benefits, social protection coverage and career development opportunities (see Messenger, 2011).[1]

As this paper focuses on firm flexibility, we will mainly analyse the effects of external and internal quantitative flexibility on the firm's innovative ability. Although it would be extremely valuable to investigate internal functional flexibility as well, the questionnaire does not provide information on it. We can only observe the share of workers who have received training, which is an indirect indicator of resources that firms utilise to enhance workers' competences. For a detailed analysis of internal functional flexibility, see for example Michie and Sheehan-Quinn (2001). However, as it is elaborated upon in the data section, our dataset provides a rich set of information on different measures of external flexibility, such as the share of temporary workers and labour turnover, and a few indicators of internal quantitative flexibility, such as the share of part-time workers. To instead account for market flexibility, i.e. to address different labour features across sectors and regions, we will add (when appropriate) sector and area dummies in the various regressions of our econometric analysis.

We expect the consequences of greater flexibility to depend strongly on firm characteristics. In particular, we consider separately firms from the high-tech and low-tech sectors, based on previous econometric analyses that highlight important differences between the two types of firms (Benfratello *et al.*, 2008; Parisi *et al.*, 2006; Mohnen *et al.*, 2006). More precisely, we expect external flexibility to have a strong negative effect for firms in high-tech sectors and a mild effect, either positive or negative, for firms in low-tech sectors. For the former type of firm, in fact, long-term relationships are more important to develop (tacit) knowledge and skills. Moreover, in such cases, the possibly negative impact of flexibility on human capital may be a more serious concern. On the other hand, we expect firms that employ more tenured workers and have a greater degree of internal flexibility to show a better ability to innovate in both types of firms. The predictions for internal quantitative flexibility, for the reasons outlined above, are instead less clear (see Table 1).

3. Literature review

The divide in labour market flexibility (internal versus external) is also reflected in the theoretical literature, which mostly focuses on the role of dismissal restrictions (i.e. external flexibility) on firm productivity and unemployment, with little or no attention given to other work arrangements (e.g. training, part-time and job rotations) and their combined use by firms. Moreover, the majority of papers are often based on a static framework without innovation, thus failing to capture the commitment aspect of work arrangements that imply internal flexibility. Here, we only mention some of them; for a more comprehensive review, see Blanchard (2006) and Bassanini *et al.* (2009).

[1] The most famous distinction of labour market flexibility is given by Atkinson (see Atkinson, 1984; Atkinson and Meager, 1986). He distinguishes flexibility depending on where flexibility occurs (inside or outside the firm) and how it is developed functionally, numerically or financially. It includes a notion of internal numerical flexibility, sometimes known as working-time flexibility or temporal flexibility. This flexibility is achieved by adjusting working hours or schedules of workers already employed within the firm. This includes part-time, flexible working hours/shifts (including night shifts and weekend shifts), working-time accounts, leaves and overtime, for example. Another form of flexibility worth mentioning is locational flexibility or flexibility of place (Wallace, 2003). This entails employees working outside the usual workplace, such as home-based workers, outworkers or teleworkers.

Table 1. *Expected relationship with innovative capacity*

	High-tech firms	Low-tech firms
External flexibility	− sig.	+ or −
Internal (functional) flexibility	+ sig.	+ sig.
Internal (quantitative) flexibility	+ or −	+ or −

For example, Poschke (2009) considers the costs of firing employees to be an exit tax that affects firms' exit decisions. They show that these costs will discourage the exit of low-productivity firms, thereby reducing the selection process and slowing the rate of productivity growth. Dolado *et al.* (2007) show in a search equilibrium model that the reduction of firing costs achieves the largest reduction in unemployment when it affects workers with lower and more volatile productivity.

However, recent theoretical papers now tend to combine different forms of labour market flexibility as well as to identify the commitments that some labour market rigidities provide for firm-specific investments. For example, MacLeod (2005) discusses several economic reasons why it may be efficient for employers and employees to enter into long-term contracts that make employee dismissal expensive. In particular, he shows that when contracts are incomplete, either because firms use subjective measures of performance or because relationship-specific investments are difficult to measure, efficiency can be enhanced with a long-term contract, which increases the cost of terminating the relationship. Belot *et al.* (2007) provide a framework in which some range of employment protections may increase workers' incentives to invest in firm-specific human capital, thus enhancing productivity growth. Cahuc and Postel Vinay (2002) show that more regulated labour markets induce human capital accumulation by increasing the proportion of skilled workers, thus leading to increased productivity and growth. They suggest that any decrease in the minimum wage should be matched by appropriate educational, industrial or employment subsidies to compensate for the possible welfare losses arising from lowering this measure. Similarly, Acemoglu and Pischke (1999) show that in non-competitive labour markets, the existence of minimum wages can increase firms' investment in training as it compresses the wage structure (i.e. the wage function increases in the level of training less steeply than productivity). The intuition behind this outcome is that a minimum wage makes it more expensive for firms to employ unskilled workers. In this setting, in fact, it is convenient for the firm to set the marginal change in profit equal to the marginal cost of training. If firms provide training to workers whose productivity is below the minimum wage, they do not have to increase wages as productivity increases and the associated profits will only go to the firms. Lastly, Haucap and Wey (2004) analyse in a dynamic framework how wage adjustments (i.e. different unionisation structures) affect firm innovation and industry employment. In particular, they show that policy makers face a trade-off between more employment and innovation activity: while decentralisation leads to higher employment levels, it also reduces innovation incentives when compared with centralised wage-setting regimes.

Similarly to the theoretical literature outlined above, the empirical literature using firm-level data is still sparse, although there are an increasing number of papers that investigate several aspects of labour market flexibility as well as their impact of firm performance and innovation. According to Kleinknecht (1998), removing labour market rigidities may be beneficial in the short term but might become harmful in the long run, because more flexibility in the labour market discourages product and process innovation, thus reducing productivity growth. In addition, softer employment protections and more flexible wage setting will give an extra advantage to non-innovative firms versus innovative firms.

In line with this assumption, Bassanini and Ernst (2002) find a negative relationship between labour market flexibility and R&D intensity in industries with a more cumulative knowledge base. The work of Kilicaslan and Taymaz (2008) also shows that countries that introduce more regulations on employment conditions, labour administration and training achieve higher levels of industrial productivity. They also find that countries with low levels of interindustry wage differentials are more successful at reallocating their resources and raising productivity. Arulampalam and Booth (2002) thoroughly investigate the relationship between fixed-term contracts and training, part-time versus full-time work, and the complementarities between education and training. According to human capital predictions, workers who are in more flexible forms of employment should be less likely than permanent workers to undergo training, as the post-training period—over which they or the employer can recoup the cost—will be of shorter duration. Consistently with this theory, they find, using data from five European countries, that the probability of receiving training is significantly lower for men with temporary contracts, whereas they did not observe any significant differences in training between part-time and full-time workers.

Recently, a growing number of empirical papers have also provided detailed evidence on the effects of internal functional flexibility for innovation. Using data on 1,900 Danish firms, Laursen and Foss (2003) test the hypothesis that human resource management positively influences firm innovation performance.[2] They conclude that changes in the organisation of the employment relationship (e.g. team-based organisation, decentralisation of decision rights, internal knowledge dissemination and quality circles) do matter for a firm to be innovative. They claim that workforce training and increased knowledge dissemination, through job rotation, for example, may be expected to stimulate a higher rate of improvement and innovation. In particular, they stress the importance of organisational requirements for coordinating the complementarities between different technologies to reap the benefits they may produce. Michie and Sheehan-Quinn (2001) rely on data collected through a survey of UK firms to test the relationship between firms' use of flexible work practices (such as the share of temporary workers), human resource management (such as compensation, recruitment and selection) and industrial relations (such as meetings with union representatives) on firm performance. Their results indicate that increased functional flexibility is positively correlated with both innovation and financial performance, whereas high labour turnover is negatively correlated with innovation only. Michie and Sheehan (2003) further extend this study to examine the effect on innovation in more detail. Their results indicate that internal functional flexibility and low labour turnover are positively correlated with all categories of innovation, whereas the use of temporary workers and fixed-term contracts is negatively correlated with process innovation.

[2] 'The term knowledge management is used to refer to the practices—implicit or explicit—used by a firm to acquire new knowledge and to rearrange and spread existing knowledge within the firm. It also includes strategies that are independent either to prevent the firm's own knowledge from "leaking" out or to encourage the dissemination of its knowledge to partner firms and others from whom the firm might benefit in mutual knowledge exchange' (Hall and Mairesse, 2006, p.10).

Kleinknecht et al. (2006) show that external flexible labour in the Netherlands, during the 1980s and 1990s, led to savings on firm wage bills, leading to the Dutch job miracle. However, they also show that this coincided with a decline of labour productivity growth—firms that have a high turnover or high shares of temporary workers do not achieve significant increases in sales growth. In addition, their analysis illustrates that firms reliant on internal flexibility were able, in spite of higher wages, to increase their productivity significantly compared with firms with rigid labour relations. This effect is particularly remarkable for firms engaged in R&D activities. In the authors' view, these results confirm the hypothesis that functional flexibility is more beneficial to innovators because it makes them more willing to invest in trust and loyalty of their personnel, which, in turn, is crucial for the accumulation of (tacit) knowledge. Lastly, using a pool of surveys from the Netherlands, Zhou *et al.* (2011) find a positive impact of internal functional flexibility on firms' new product sales (i.e. products 'new to the market'), whereas they find mixed results on numerical flexibility, with high shares of temporary workers having some positive effects for imitative products (i.e. 'new to firms'), but reducing the probability of introducing products new to the market.

From the above review of the literature, it appears clear that to fully evaluate the effects of the various labour reform measures is crucial to understand their consequences on firm innovation. The next section describes the reforms implemented in Italy in recent years, along with our dataset, and states our reasons for studying the Italian case.

4. Data description

During the 1990s a series of reforms were introduced into the labour law system in Italy, which gradually introduced new arrangements allowing greater use of labour flexibility by firms. The law known as Pacchetto Treu (named after the Labour Minister) expanded the range of admissible fixed-term contracts and initiated a phasing out of the monopoly of the Public Employment Service by opening the market to private job-placement agencies authorised to deliver job intermediation and outplacement. It also encouraged part-time employment, fixed-term training and apprenticeship contracts for young workers.[3] The Legislative Decree 61 in 2000 represented another step towards more flexible work relations and the more widespread use of part-time contracts. It introduced elastic clauses ('clausole elastiche'), which allow for changes to the temporal distribution of original hours, as well as extra hours ('lavoro supplementare'), allowing employees to work longer hours than originally agreed upon.[4]

In particular, in this work, we rely on two waves, the eighth (1998–2000) and ninth (2001–03), of the comprehensive survey on Italian manufacturing firms carried out by the UniCredit–Capitalia banking group (and previously by Mediocredito Centrale), which covers the period immediately following the June 1997 Pacchetto Treu (Law 196) and the period before and after the transposition of the EU Directive 93/104 on working time (Legislative Decree 61). In 2003, further changes were introduced by the so-called Legge Biagi (Legislative Decree 276). However, this reform occurred at the end of our sample period and thus we can neglect it for the scope of the present analysis (see Table 2).

[3] The search for increased flexibility has also been directed towards a range of labour and product market institutions, to the wage-setting process, as well as administrative rules (industrial action procedures, internal union organisation and financing and administrative simplification).

[4] For a detailed description of these reforms, see Emanuele *et al.* (2001).

Table 2. *Labour market reform*

	Legislation	Reform
External flexibility		
Full temporary	Law 196 changed the time frame within which a renewal of the contract would have implied a transformation of the temporary contract into a permanent one. In 2001, Law 368 removed further constraints to the use of such contracts but introduced a temporal limit for the duration of the contract, which is three years. With the worker's consent, it is possible to extend the length of the contract for three additional years.	Pacchetto Treu (1997)
Collaboration	The use of such a contract was based on a loophole that firms have found in the system of labour laws to hire workers on a flexible basis. It had not been regulated by any specific law until 2003, when Legislative Decree 276 (also known as Legge Biagi) introduced legislation regarding collaborations upon a project ('contratti a progetto').	
Manpower	Law 196 authorised private agencies to deliver job intermediation. This contract involves three subjects: the firm, the worker and the agency. The worker is hired and paid by the agency, which sends him on assignment to work at the firm for a period of time.	Pacchetto Treu (1997)
Apprenticeship	This contract allows a firm to hire young workers on a lower wage basis in exchange for 'training on the job'. However, many firms have not regularly offered proper training. Law 196 (and subsequently Legislative Decree 276) has modified the requirements to ensure that firms give training.	Pacchetto Treu (1997)
Internal flexibility		
Part-time	This contract provides a working time that is lower than the typical 'normal or full-time working schedule, which is equal to 40 hours per week, according to Legislative Decree 61. It can either be on a permanent or temporary basis.	Legislative Decree 61 (2000)

The surveys have been conducted through questionnaires administered to a representative sample of Italian firms in the years 2000 and 2004, and although from some questions it is possible to obtain yearly data, the majority of the information refers to the previous three-year periods (i.e. 1998–2000 and 2001–03). For the majority of firms, the survey is supplemented with standard balance sheet data.[5] The sample is stratified with references to the number of employees, goods/services sector and geographical area. Firms with more than 500 employees are included in each wave. Most of the firms with less than 500 employees are selected with a stratified method

[5] The principal information contained in the questionnaire concerns general news on the company, its ownership, controlling interests and group memberships, the workforce, investment activities, technological innovation, R&D, internationalisation, commercial and competitive channels, and finance (see the survey of manufacturing enterprises, http://www.unicredit-capitalia.eu).

in each wave, but the decision to retain some of them for two consecutive waves is at the discretion of UniCredit. Using two waves allows to control for a firm's unobserved fixed effect, while using a three-wave or longer panel would greatly reduce the number of firms and introduce problems (Annamaria Nese and O'Higgins, 2007). However, throughout the analysis, we will rely on sampling weights to extend the results to the overall population of Italian manufacturing firms and to avoid inaccurate estimates and standard errors (Gelman, 2004).

The eighth and the ninth surveys include, respectively, 4,289 and 4,497 firms. To broaden the sample period of our analysis, we merged these two waves and obtained a reduced balanced sample of 2,091 firms. This sample includes only those firms existing in both surveys and, hence, with potentially complete observations over the 1998–2003 period. We will progressively use the data panel structure to check and address endogeneity problems. Specifically, we rely on a model that distinguishes between a firm's propensity to innovate and innovation intensity. We will measure the firm's innovative propensity by means of a dummy variable for new processes and new products introduced into the market, whereas firm innovation intensity can be measured by the share of innovative sales in total sales.[6] The questionnaire also provides information for other important variables generally used in innovation studies. See Table A1 in the Appendix for a complete description of the variables used in the econometric analysis. However, contrary to other types of surveys (e.g. the Community Innovation Survey), it is not possible to distinguish between innovative sales corresponding to products that are new for the firm but possibly known to the market, which can be considered imitations of products already produced by other competitors, and those corresponding to products that are new to the market, which can be regarded as true innovations (see also Zhou *et al.*, 2011).

Based on this sample, Table 3 reports the population percentages (and standard errors) of firms that introduced an innovation (either product or process innovation). The most important information is the increasing percentage of innovative firms, across size and sector, over the period considered (the only exception is the percentage of firms with more than 500 employees). These higher percentages reflect the higher number of firms carrying out R&D. As Table 4 shows, particularly in high-tech industries, the majority of firms are involved in R&D activities. This is even more visible for larger firms where this percentage reaches 94% in high-tech sectors.[7]

With regard to the work arrangements available in the questionnaire and then used in our econometric analysis, we can observe the following variables:

1. External (numerical) flexibility
(a) *Full-time temporary*: the percentage of workers under a working contract with a temporal limit of three years, which can be extended for three additional years;
(b) *Collaboration*: the percentage of workers hired on a flexible basis to collaborate on a project without being directed. Although these workers might work regularly for one or more employers, they are not on payroll;

[6] Firms are classified to have introduced an innovation by means of the following question: '*During the three-year period (2001–2003) has the firm introduced: a process innovation; a product innovation; organisational innovation related to process innovation; organisational innovation related to product innovation?*' Firm innovation intensity is determined by means of the following question: '*Which is the share of sales stemming from innovative products in year 2003?*'

[7] Firms were classified according to Parisi *et al.* (2006) and Benfratello *et al.* (2008) in (i) low-tech sectors (textile, wood, food, plastic, paper, coke, non-metallic and 'not elsewhere classified') and (ii) high-tech sectors (vehicles, machinery and chemicals).

Table 3. *Percentage of firms introducing an innovation*

Firm size	**Low-tech**		**High-tech**	
(*n* employees)	**1998–2000**	**2001–2003**	**1998–2000**	**2001–2003**
11–20	0.34 (0.020)	0.46 (0.021)	0.47 (0.037)	0.52 (0.036)
21–50	0.39 (0.023)	0.52 (0.023)	0.55 (0.035)	0.70 (0.032)
51–250	0.58 (0.041)	0.66 (0.082)	0.71 (0.042)	0.08 (0.032)
251–500	0.61 (0.104)	0.83 (0.068)	0.82 (0.060)	0.87 (0.054)
>500	0.80 (0.062)	0.76 (0.067)	0.90 (0.040)	0.90 (0.055)

Notes: Standard errors are given in parentheses. Sample size: 2091.
Estimations refer to the overall population of Italian firms.

Table 4. *Percentage of firms conducting R&D*

Firm size	**Low-tech**		**High-tech**	
(*n* employees)	**1998–2000**	**2001–2003**	**1998–2000**	**2001–2003**
11–20	0.21 (0.017)	0.22 (0.017)	0.34 (0.036)	0.46 (0.036)
21–50	0.22 (0.019)	0.33 (0.021)	0.53 (0.036)	0.60 (0.034)
51–250	0.40 (0.040)	0.51 (0.033)	0.77 (0.039)	0.79 (0.033)
251–500	0.58 (0.103)	0.72 (0.080)	0.75 (0.075)	0.85 (0.058)
>500	0.80 (0.064)	0.73 (0.079)	0.86 (0.058)	0.94 (0.045)

Notes: Standard errors are given in parentheses. Sample size: 2091.
Estimations refer to the overall population of Italian firms.

(c) *Manpower*: the percentage of workers hired and paid by an agency that sends them on assignment to work at the firm for a period of time;
(d) *Apprenticeship*: the percentage of young workers hired on a lower-wage basis in exchange for 'training on the job';[8]
(e) *Turnover*: the percentage of workers leaving and entering an organisation in each survey (i.e. $\frac{hirings + leavings}{number\,of\,employees}$);

2. Internal (quantitative) flexibility

(a) *Part-time*: the percentage of workers with daily working time lower than 'normal' ('horizontal' part-time) or who works only on certain days, weeks or months of the year ('vertical' part-time), either on a permanent or temporary basis;

3. Internal (functional) flexibility

(a) *Training*: the share of employees that received training.

Table 2 summarises the legislation that applies to these working arrangements, along with the name of the law that modifies their regulation during the period of our

[8] However, many firms have not regularly given the proper training.

Table 5. *Percentage of work arrangements*

Work arrangements	Low-tech		High-tech	
	1998–2000	**2001–2003**	**1998–2000**	**2001–2003**
Part-time temporary	0.027 (0.026)	0.002 (0.007)	0.0001 (0.001)	0.002 (0.005)
Part-time permanent	0.047 (0.003)	0.040 (0.002)	0.053 (0.010)	0.031 (0.002)
Full-time temporary	0.001 (0.0001)	0.034 (0.004)	0.005 (0.001)	0.022 (0.004)
Collaboration	0.061 (0.007)	0.043 (0.003)	0.076 (0.008)	0.049 (0.004)
Training	0.026 (0.002)	0.046 (0.003)	0.037 (0.003)	0.059 (0.006)
Turnover	0.279 (0.027)	0.200 (0.010)	0.211 (0.040)	0.176 (0.021)
Manpower	0.034 (0.002)	0.042 (0.004)	0.032 (0.003)	0.037 (0.005)
Apprenticeship	0.017 (0.001)	0.012 (0.001)	0.023 (0.002)	0.013 (0.001)

Notes: Standard errors are given in parentheses. Sample size: 2091.
Estimations refer to the overall population of Italian firms.

investigation. Two of these variables warrant remarks: *training* and *turnover*. The variable *training*, despite being only an indirect measure of internal functional flexibility, still allows accounting for those firms that invest more in their internal job market. Thus, it is an important indirect indicator of internal functional flexibility. The variable *turnover* may capture additional information with respect to the variables measuring the various work arrangements. Specifically, it also captures instances of voluntary leave, which may reflect the worker's attitude towards the external job market in different types of firms.[9]

Table 5 reports the share of workers hired relying on different work arrangements by low-tech and high-tech firms in the period considered. For high-tech firms there was a significant increase in the share of workers hired on a part-time and full-time temporary basis (at the 1% level), a significant decrease in the share of workers hired on a part-time permanent basis and with a contract of collaboration (at the 5% and 1% levels), and a significant increase in the share of workers who received training (at the 1% level). For low-tech firms there was a significant increase in the share of workers hired on a full-time temporary basis and coming from manpower agencies, a significant reduction in labour turnover and in the share of workers hired with a collaboration contract (at the 1% and 5% levels), and a significant increase in the share of workers who received training. In general, these descriptive statistics suggest a greater use of flexible contracts in both types of firms. However, high-tech firms seem to prefer internal flexibility compared with low-tech firms. In both types of firms, though, we can observe an increase in the share of workers who received training.

As some authors have suggested (Boeri and Garibaldi, 2007; Daveri, 2004), such reforms were asymmetric and introduced a dual labour market in Italy: the use of fixed-term contracts kept the legislation applied to the stock of workers largely untouched and changed the regulations only for a subset of workers.[10] Subsequent to these reforms, Italy, as well as other European countries that introduced a dual-labour market,[11] experienced—thanks to the significant contribution of fixed-term

[9] Thanks to the referees for pointing out the peculiarity of these two variables.

[10] The share of workers with non-standard contracts comprises about 14% of the total labour force, mainly young people, although recent trends highlight the use of these contracts among older cohorts (see Madia, 2009).

[11] Belgium, Spain, the Netherlands, Germany, Sweden and Portugal (see Boeri and Garibaldi, 2007).

contracts—protracted employment growth despite moderate output growth, which means a decline in labour productivity growth.[12] These authors interpret these results as the negative effects of fixed-term contracts on labour productivity, as these flexible arrangements induced a change in the workforce composition, the entry of low-skilled workers and/or workers with low schooling levels (i.e. primary or lower lever). Recently, Lucidi and Kleinknecht (2010) found evidence that Italian firms with a higher share of flexible workers experienced a reduction in labour productivity growth. In the recent literature, there is also evidence that recent reforms achieved the aim of reducing wage cost pressure (Picchio, 2007).

As Kleinknecht et al. (2006) argued for the Netherlands, we argue that a major transmission channel from lower wage growth and flexible labour to low productivity growth is represented by the effects on firm innovative activity. In fact, these reforms—while allowing greater labour flexibility—may have strongly affected firm innovative strategies as well and, hence, one of the key factors enabling firms to survive and grow. In the next section, we illustrate the econometric model and incorporate the variables describing worker arrangements in more refined econometric estimations of firm innovative capacity.

5. The empirical model and results

We adopt a generalised (type II) Tobit model consisting of two equations, where the first one is a probit equation determining whether a firm innovates or not ('propensity to innovate') and the second one is a linear regression ('intensity to innovate') explaining how much the firm innovates (Mohnen *et al.*, 2006). Denoting by y_{1i}, the binary variable indicating if firm i is an innovative firm—i.e. a dummy variable indicating whether the firm has introduced at least one product or process innovation—we can write

$$y_{1i} = \begin{cases} =1 & if \quad y_{1i}^{*} > 0 \\ =0 & if \quad y_{1i}^{*} \le 0 \end{cases} \tag{1}$$

where $y_{1i}^{*} = x_{1i}b_1 + u_{1i}$ is a latent variable that represents the incentives to innovate. x_{1i} is a vector of explanatory variables, b_1 is a vector of the parameter to be estimated and u_{1i} is a random error term, which includes the effect of omitted variables. As explanatory variables x_{1i}, in addition to the amount of resources spent on R&D per employee (*R&D expenditure*) and fixed capital per employee (*K investment*), we use industry and area dummies, firm size and age (*Size* and *Age*). Industry dummies capture technological opportunity conditions, industry-targeted innovation policies and industry-specific labour market features as well as differential demand growth effects. Size reflects access to finance, scale economies and differences in work organisation (Mohnen *et al.*, 2006). To account for the fact that young firms grow faster, we also add a dummy for firms that are less than three years old (*Young*). It is valuable to include a dummy as well for firms that underwent structural changes during the period of analysis (*M&As*), to account for exceptional events in the life of the firm, and for

[12] For an investigation of the effects of employment protection on firm productivity in the USA, see Autor *et al.* (2007).

firms operating in international markets (*International competition*) and that have developed technical agreements with foreign firms (*International agreements*), to account for firms' innovation strategies in international markets (Archibugi and Michie, 1995). As the main objective of our investigation is to study how labour market regulations affect firm innovativeness, we estimate the probability to be innovative, including in the explanatory set, x_{1i}, variables that represent

(i) the internal flexibility: *Part-time temporary*, *Part-time permanent* and *Training*;
(ii) the external flexibility: *Full-time temporary*, *Manpower*, *Collaboration*, *Apprenticeship* and *Turnover*.[13]

The second equation of the Tobit (type II) model is specified in terms of a second latent variable y^*_{2i}, which is equal to the actual share of innovative sales y_{2i} if the firm is innovative (i.e. $y^*_{1i} > 0$). Because the share of innovative sales is bounded by 0 and 1, it is preferable to perform a logit transformation of the data and express this second equation in terms of the latent logit-share variable $z^*_{2i} = ln(y^*_{2i} / (1 - y^*_{2i}))$, which varies from $-\infty$ to $+\infty$.[14] Thus we can write our second equation

as
$$z_{2i} = \begin{cases} = z^*_{2i} & if \quad y^*_{1i} > 0 \\ = undefined & if \quad y^*_{1i} \leq 0 \end{cases} \tag{2}$$

or equivalently
$$y_{2i} = \begin{cases} = e^{z^*_{2i}}/(1 + e^{z^*_{2i}}) & if \quad y^*_{1i} > 0 \\ = 0 & if \quad y^*_{1i} \leq 0 \end{cases} \tag{3}$$

where $z^*_{2i} = x_{2i}b_2 + u_2$. x_2 is a vector of explanatory variables, b_2 is a vector of parameters to be estimated and $u_{2i} > 0$ is an error term reflecting omitted variables. Because we have data on sales growth, we decide to exploit the data panel structure in order to exclude the variable 'past sales growth' (g_sales_{t-1}) from the explanatory variables we have in x_{2i} and to include it in x_{1i}. This variable, in fact, can be a decisive factor of innovation, reflecting stronger demand and easier internal and external access to finance (Mohnen *et al.*, 2006; Cainelli *et al.*, 2006). Assuming that u_1 and u_2 are bivariate normal with zero mean and $\sigma_{u1} = 1$, we can estimate the model as a generalised Tobit (type II) model using the Heckman selection procedure for survey analysis. Therefore, estimations refer to the population of Italian firms. Results for the baseline model without considering any labour variables are reported in Table 6. These results suggest the plausibility of the model, as it is indicated by the significance level of the selection variable g_sales_{t-1}, and problems of selection, as the ρ coefficient indicates.[15] The results for the traditional regressors are in line with the literature. Larger firms and firms facing international competition are more likely to introduce innovation. Firms with higher spending on R&D and fixed investment are also more likely to be innovative and have a higher percentage of sales stemming from innovative products. International agreements also positively affect firms' ability to innovate.

[13] See Section 4 for a description of these work arrangements.

[14] Since the variable z is not defined when y_2 is equal to 1, we set in this case the value of y_2 equal to 0.99.

[15] If $\rho = 0$, the sum of the likelihood from estimating the two equations separately will equal the likelihood of the model with sample selection, i.e. a *t*-test for $\rho = 0$ is equivalent to the likelihood ratio test.

Table 6. *Heckman base results (cross section)*

	Intensity Equation (2)		**Propensity** Equation (1)	
R&D expenditure	0.2228***	(0.024)	0.1605***	(0.032)
K investment	0.0232**	(0.010)	0.0235***	(0.006)
Age	0.0022	(0.006)	0.0010	(0.003)
Young	−0.8054	(1.508)	−0.0760	(0.436)
Size	0.0004	(0.000)	0.0026***	(0.001)
M&As	0.7655**	(0.309)	0.1686	(0.141)
Patents bought	−0.0729	(0.505)	0.0949	(0.288)
Patents sold	−1.3512*	(0.756)	−0.6609*	(0.338)
International agreements	0.3054	(0.316)	0.3946**	(0.173)
International competition	0.1094	(0.201)	0.2000**	(0.101)
Constant	−5.9344***	(1.100)	−0.6630**	(0.267)
g_sales_{t-1}			0.3475**	(0.167)
σ	1.6345***	(0.164)		
ρ	0.8570***	(0.073)		
Log-likelihood	−39,213.29			
N	639		1417	

Notes: In the propensity equation the dependent variable is a dummy variable that takes value 1 if the firm has introduced at least one product or process innovation, whereas in the intensity equation the dependent variable is a logit transformation of the actual share of innovative sales. The exclusionary variable is g_sales_{t-1}.

Regressions include sector and area dummies.

$^{*}p < 0.10$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

In Table 7, results for the model controlling labour variables are reported. In column (*a*) we introduce variables measuring internal flexibility (functional and quantitative). These variables, which are jointly significant at the 5% level, seem to positively affect both firm propensity to innovate and firm innovation intensity. For example, the mere increase by 5% in the percentage of workers who receive training is associated with an increase by 2% in the share of innovative sales.[16] In column (*b*) we additionally introduce variables accounting for external flexibility. These variables are also jointly significant, though their effects are more variegated. Some of them (e.g. *Apprenticeship*) seem to have a positive effect, whereas others (e.g. *Collaboration*) seem to have a negative impact on firms' ability to innovate. Lastly, in column (*c*) we introduce labour variables in interactions with a dummy variable for high-tech firms. For high-tech firms we observe that part-time workers positively affect the percentage of new products in total sales at the 1% level, whereas a higher labour turnover has a negative impact on the probability to innovate at the 10% level. This latter result is probably due to the difficulties of developing long-term and trust-based relations when labour turnover is excessively high. This, in turn, might affect firms' ability to

[16] In this case, the estimate of b_2 needs to be back-transformed from the logit scale on the probability scale (which is bounded between (0,1)), i.e. $\frac{exp(b_2 x)}{1+exp(b_2 x)}$.

Table 7. *Estimation results: adding labour variables (cross section)*

	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)
	a		*b*		*c*	
R&D expenditure	0.218***	0.160***	0.202***	0.177***	0.207***	0.180***
	(0.024)	(0.032)	(0.025)	(0.034)	(0.026)	(0.035)
K investment	0.022**	0.024***	0.005	0.019***	0.004	0.020***
	(0.010)	(0.006)	(0.010)	(0.007)	(0.010)	(0.007)
Age	0.002	0.001	0.001	−0.001	0.001	−0.002
	(0.006)	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)
Young	−0.780	−0.071	0.135	−0.850**	0.068	−0.983**
	(1.535)	(0.445)	(2.338)	(0.427)	(2.676)	(0.440)
Size	0.000	0.003***	−0.000	0.002***	−0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
M&As	0.719**	0.168	0.505*	0.031	0.515*	0.023
	(0.315)	(0.143)	(0.297)	(0.145)	(0.296)	(0.148)
Patents bought	−0.050	0.091	0.132	0.244	0.103	0.272
	(0.512)	(0.281)	(0.495)	(0.300)	(0.500)	(0.301)
Patents sold	−1.280*	−0.670**	−1.437*	−0.551	−1.227	−0.503
	(0.761)	(0.336)	(0.833)	(0.403)	(0.905)	(0.425)
International agreements	0.250	0.389**	0.340	0.501**	0.374	0.522***
	(0.323)	(0.174)	(0.334)	(0.199)	(0.337)	(0.200)
International competition	0.108	0.185*	0.125	0.252**	0.159	0.268**
	(0.204)	(0.102)	(0.213)	(0.117)	(0.213)	(0.119)
Part-time permanent	1.490	0.472	0.533	0.138	1.142	0.355
	(1.291)	(0.541)	(1.399)	(0.610)	(1.353)	(0.632)
Part-time temporary	1.131	2.682**	2.728	4.208***	0.733	3.917***
	(2.340)	(1.131)	(2.758)	(1.129)	(1.849)	(1.275)

Table 7. *Continued*

	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)
	a		*b*		*c*	
Training	1.614**	0.349	1.060	0.228	1.716	0.361
	(0.666)	(0.312)	(0.726)	(0.357)	(1.306)	(0.517)
Full-time temporary			1.798**	0.493	1.374	0.364
			(0.876)	(0.393)	(1.047)	(0.442)
Manpower			−0.377	0.430	−0.600	0.399
			(0.965)	(0.464)	(1.223)	(0.549)
Collaboration			−0.246	−0.442	−2.198	−1.118
			(1.252)	(0.632)	(1.630)	(0.864)
Apprenticeship			5.337*	2.981**	8.069**	4.508***
			(2.770)	(1.296)	(3.171)	(1.339)
Turnover			−0.081	0.018	0.055	0.093
			(0.147)	(0.088)	(0.096)	(0.057)
Part-time permanent × HT					−3.977	−1.534
					(4.282)	(1.933)
Part-time temporary × HT					25.662***	3.154
					(9.872)	(4.931)
Training × HT					−0.818	0.333
					(1.553)	(0.835)
Full-time temporary × HT					1.435	0.720
					(1.424)	(0.863)
Manpower × HT					1.610	0.309
					(1.844)	(1.022)
Collaboration × HT					5.163*	2.204
					(2.671)	(1.720)

Table 7. *Continued*

	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)	Intensity Equation (2)	Propensity Equation (1)
	a		*b*		*c*	
Apprenticeship × HT					−10.281*	−5.246*
					(6.037)	(2.743)
Turnover × HT					−2.115	−1.129*
					(1.305)	(0.637)
g_sales_{t-1}		0.323*		0.319*		0.327*
		(0.166)		(0.189)		(0.194)
Constant	−4.574***	−0.644***	−4.493***	−0.574**	−4.349***	−0.486*
	(0.497)	(0.207)	(0.510)	(0.248)	(0.584)	(0.283)
Log-likelihood	−38,927.97		−30,470.87		−30,257.21	
N	769	1405	554	1097	554	1097
σ	1.651***	(0.162)	1.574***	(0.177)	1.550***	(0.189)
ρ	0.855***	(0.073)	0.812***	(0.079)	0.794***	(0.080)

Notes: In the propensity equation the dependent variable is a dummy variable that takes value 1 if the firm has introduced at least one product or process innovation, whereas in the intensity equation the dependent variable is a logit transformation of the actual share of innovative sales. The exclusionary variable is g_sales_{t-1} .
Regressions include sector and area dummies.
*$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$.

take advantage of innovations or to promote innovation, not sufficiently investing in those able to carry out R&D.

5.1 Propensity to innovate and work arrangements

Relying on the same set of (time-varying) variables used in the previous section and by completely exploiting the data panel structure, in this section we will estimate a probability model for the introduction of a product or a process innovation (i.e. a conditional logit for equation (1) only) to investigate the effects of different labour arrangements while controlling for endogeneity issues.[17] Given that we only have two observations concerning the introduction of innovation, it is impossible to fully address the endogeneity problems and to identify causal links. However, because one fundamental problem is to control for unobserved firm characteristics that are constant over time, the conditional logit model will work properly. Conditional logit models eliminate firm-specific effects, but only switchers (i.e. firms that introduced an innovation in just one of the two sub-periods) contribute to the likelihood function. Therefore, we can rely on a restricted number of observations. Indeed, we cannot account for another potential source of endogeneity caused by technological shock that leads, for example, to an increase in both the probability of observing an innovation and research intensity or the use of labour flexibility (Parisi *et al.*, 2006). Table 8 reports results for the conditional model, where, in column (1′), we re-estimate the model of column (1), replacing *R&D expenditure*, the variable measuring the amount of resources spent on R&D per employee, with a dummy variable for R&D (*Dummy R&D*), as there were firms reported to do R&D that were unable to indicate how much they spent on this purpose. Likewise, *Dummy investment* is a dummy variable equal to 1 that replaces *K investment* for firms that declared investment in fixed capital but did not indicate the amount. On the whole, results are substantially similar to the cross-sectional analysis. For high-tech firms, some variables representing external flexibility have a negative effect in explaining the probability of introducing process or product innovations. In particular, the percentage of workers coming from manpower agencies is negative and significant at the 10% level. For example, for high-tech firms, an increase by 5% in the percentage of manpower workers is associated with a decrease by 3% in the probability to introduce an innovation.[18] The variable accounting for internal quantitative flexibility is again positive and significant for both groups of firms, but for high-tech firms this effect is significantly higher. Furthermore, the results for the traditional regressors are in line with those in the cross-sectional analysis. These regressions confirm the importance of work arrangements in affecting firms' innovative capacity and reinforce previous results. In particular, the variables representing internal flexibility again have positive effects on firms' ability to innovate for both high-tech and low-tech firms. Concerning external flexibility, especially for high-tech firms, some variables

[17] As in the previous section, we calculated the mean of the labour variables—where available—over three/two years. Whenever we did not observe any response for the three years in the 1998–2000 period, we assumed a value of zero. Because the assumption seems reasonable according to the questionnaire structure, this was done to obtain a proper sample size.

[18] In formula, $P(y_1 = 0, y_2 = 1 \mid y_1 + y_2 = 1) = exp(\beta(x_2 - x_1))/(1 + exp(\beta(x_2 - x_1))) = exp((4.1310 * 0.05)$ $+(-6.2195 * 0.05))/(1 + exp((4.1310 * 0.05) + (-6.2195 * 0.05)) = 0.47$ compare to 0.5, should the percentage of manpower workers remain equal (see Cameron and Trivedi, 2007, p. 797).

Table 8. *Conditional logit results*

	Propensity Equation (1)		Propensity Equation (1′)	
R&D expenditure	0.3152***	(0.098)		
K investment	−0.0009	(0.001)		
Dummy R&D			1.2120***	(0.267)
Dummy investment			1.3289***	(0.394)
Age	0.4908***	(0.161)	0.6837***	(0.158)
Size	0.0035	(0.005)	−0.0006	(0.004)
M&As	1.0311**	(0.430)	0.6487	(0.424)
Patents bought	0.8174	(0.916)	0.9447	(0.728)
Patents sold	0.0547	(0.972)	0.6786	(0.996)
International agreements	1.3393*	(0.697)	1.5433**	(0.716)
International competition	−0.1349	(0.482)	−0.2507	(0.374)
Part-time temporary	0.2047***	(0.060)	0.2113**	(0.087)
Part-time permanent	−3.6031	(2.955)	−1.6080	(1.728)
Training	−0.4028	(1.113)	0.0983	(1.140)
Full-time temporary	−0.1915	(1.009)	−0.9760	(0.880)
Manpower	2.1012	(1.946)	4.1310*	(2.386)
Collaboration	3.0891*	(1.717)	2.3665	(1.622)
Apprenticeship	0.2355	(2.357)	−0.6020	(2.210)
Turnover	0.1164	(0.229)	0.6866	(0.758)
Part-time temporary × HT	59.9428*	(30.924)	49.0515	(38.274)
Part-time permanent × HT	4.4792	(3.034)	1.7010	(1.868)
Training × HT	0.5973	(1.971)	0.5667	(1.840)
Full-time temporary × HT	3.4216	(6.173)	5.4318	(5.057)
Manpower × HT	−2.3126	(3.072)	−6.2195*	(3.559)
Collaboration × HT	−1.1162	(2.906)	−0.4999	(2.668)
Apprenticeship × HT	0.5919	(3.294)	2.0681	(3.120)
Turnover × HT	1.3165	(1.570)	0.9026	(1.342)
Log-likelihood	−3,608.246		−4,522.71	
N	638		808	

Notes: In this model, only switchers—i.e. firms that have introduced an innovation in just one of the two periods—contribute to the likelihood function. It controls for unobserved firm characteristics that are constant over time. The dependent variable is a dummy variable equal to 1 if the firm introduced an innovation in just one of the two periods.

*$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$.

were negative and significant, suggesting that they may have negative effects on firms' ability to innovate.

5.2 Intensity to innovate and work arrangements: a panel data selection estimator

In recent years, a number of panel estimators have been suggested for sample selection models, where both the selection equation and the equation of interest contain individual effects correlated with explanatory variables (Dustmann and Rochina-Barrachina, 2007; Raymond *et al.*, 2010). Relying on this literature, in this paragraph we fully exploit the panel structure of our dataset by estimating a selection model where both the selection and regression equations may contain firm effects correlated to unobservables. In particular, we utilise the two-step estimator proposed by Rochina-Barrachina (1999), which extend Heckman's sample selection technique developed in the first part of Section 5 to the case where one correlated selection rule in two different time periods generated the sample. The purpose of using this estimator is to eliminate the individual effects from the equation of interest by taking time differences and then condition upon the outcome of the selection process being 'one' (observed) in the two periods (Rochina-Barrachina, 1999). In the first step, two correction terms must be estimated, the form of which depends upon the assumption made about the selection process and the joint distribution of unobservables. By noting that for a firm that is innovative in two periods, and has therefore been selected into the second-stage estimation, first-differencing eliminates the firm effect from equation (2), and with consistent estimates of the two correction terms, simple least squares can be used to obtain consistent estimates in the second step. More precisely, the estimated equation is now given by

$$z_{i2} - z_{i1} = b_2(x_{i2} - x_{i1}) + l_{12}\lambda_1(.) + l_{21}\lambda_2(.) + v_{i21}$$

$$\Delta z_{i21} = b_2 \Delta x_{i21} + l_{12}\lambda_1(.) + l_{21}\lambda_2(.) + v_{i21} \tag{4}$$

where the subscript now indicates times 1 and 2, and λ_1 and λ_2 are the correction terms. To construct estimates of the λ terms, a bivariate probit of equation (1) is estimated in the first step for the two waves. Then, only for the subsample with $y_2 = y_1 = 1$, we carry out a regression of Δz on Δx and $\hat{\lambda}$ to estimate the parameters of interest. Results for the bivariate probit (not reported) indicate a positive and significant coefficient of correlation (0.20) between the two equations. Table 9 reports results for the second stage, where standard errors have been corrected to account for first-stage estimations. Though this estimator reduces the number of available observations in the second step, these regressions are useful to make comparisons with the cross-sectional analysis conducted above.[19] In line with the cross-sectional analysis, the percentage of workers who received training is positive and significant at the 1% level. Again, the mere 5% increase in the percentage of workers who receiving training, for example, is associated with an increase of 4% in the mean share of innovative sales.[20] The most striking result for firms in high-tech sectors is the variable accounting for labour turnover, which is again negative and significant at the 5% level. For low-tech firms, however, some variables measuring external flexibility were also positive and significant (i.e. full-time workers on a temporary and collaboration basis). In contrast with the cross-sectional analysis, for high-tech firms, the share of workers with a collaboration contract is now negative and highly significant.[21] Overall, these combined results suggest the presence of an optimal combination of internal and external flexibility, with respect to which an excessive

[19] In any case, even in a small sample, this estimator is less biased than the estimator ignoring correction for sample selection. Monte Carlo analysis also showed that the estimator is (i) robust to violation of conditional exchangeability (i.e. sample selection varying over time), (ii) free from misspecification affecting the individual effects in both equations, (iii) robust to correlation among variables over time and (iv) robust to violation of the normality assumption (Rochina-Barrachina, 1999).

[20] See footnote 16.

[21] In addition to correlation with the firm fixed effect, this result might also be due either to the change in the way the question is asked in the ninth wave, wherein it is split into two parts, compared with the eighth, or to the change in the law, which became more stringent (although at the very end of our sample). Therefore, we check the robustness of our results by taking into account the bounded nature of the variable measuring the share of innovative products in total sales. Recently, Papke and Wooldridge (2008) proposed an estimator for fractional response variables for a panel data set with a large cross-sectional dimension and relatively few time periods, which allows for time-constant unobserved effects that can be correlated with explanatory variables. Although not significant, the variable accounting for the share of workers with a collaboration contract again has a negative sign.

Table 9. *Heckman panel estimator*

	Intensity Equation (2)	
Δ **R&D expenditure**	0.047***	(0.0257)
Δ **Investment**	−0.041***	(0.0002)
Δ **Age**	−1.457***	(0.7283)
Δ **Size**	0.001***	(0.0004)
Δ **M&As**	−0.332	(0.3386)
Δ **Patents bought**	0.113	(0.1257)
Δ **Patents sold**	0.192	(1.1189)
Δ **International agreements**	−0.088	(0.1936)
Δ **International competition**	−0.013	(0.6852)
Δ **Part-time temporary**	14.133	(24.1395)
Δ **Part-time permanent**	−1.410	(2.9545)
Δ **Training**	3.000 ***	(0.676)
Δ **Full-time temporary**	3.438 ***	(1.4962)
Δ **Manpower**	0.864	(7.3087)
Δ **Collaboration**	9.599 ***	(2.0293)
Δ **Apprenticeship**	0.147	(5.1563)
Δ **Turnover**	0.276	(0.993)
Δ **Part-time temporary × HT**	−7.285	(28.7783)
Δ **Part-time permanent × HT**	−1.425	(4.1134)
Δ **Training × HT**	−1.763	(2.4579)
Δ **Full-time temporary × HT**	−1.248	(3.4785)
Δ **Manpower × HT**	0.646	(4.1474)
Δ **Collaboration × HT**	−9.661***	(2.8462)
Δ **Apprenticeship × HT**	2.416	(2.157)
Δ **Turnover × HT**	−1.389**	(0.7724)
λ_1	0.207	(0.3203)
λ_2	1.254**	(0.6911)
1st step observation	785	
2nd step observation	142	

Notes: Two-stage pane estimation. The first step (not reported) is a bivariate probit using all of the observations to estimate λ_2 and λ_1. In the second step, for the subsample of firms that innovate in both periods, i.e. with λ_2 and $d_1 = 1$, we carried out least squares analysis of $d_2 = 1$ on Δy, Δx and λ_1 λ_2.

*$p < 0.10$, **$p < 0.05$ and ***$p < 0.01$.

Source: Rochina-Barrachina (1999).

use of flexibility (e.g. too many workers entering and leaving the firm) may have—especially in high-tech sectors—counterpositive effects on the firm's ability to innovate.

6. Conclusions

In modern economies, a firm's innovative behaviour and worker competences are inextricably linked. A firm that fails to develop employees' skills or to select and allocate competent people risks finding it more difficult to implement new technologies and spread innovation across the firm, thus preventing workers from understanding and producing innovative products and processes. Training leads, instead, to an increase in labour quality by equipping employees with greater skills and knowledge. This makes the practices—implicit or explicit—used by firms to acquire new knowledge, and the re-arrangement and dissemination of existing knowledge within the firm (human management practices), an important strategic resource. The aim of this study was to test in which way flexible labour arrangements influence—by affecting the long-term relationship between firms and workers—the firm's ability to innovate. Because there might be valuable differences, both in terms of costs and workers' attitudes towards firms, we distinguish between two different kinds of flexibility: internal and external. Internal flexibility (especially functional) does not necessarily yield wage cost savings and, on the contrary, might even lead to a significant increase when it involves employee training. From this perspective, for example, part-time work can also be used to accommodate working hour preferences and enhance loyalty as well as training or educational breaks. External flexibility aims, instead, at the numerical adaptation of the number of workers required by firms, by allowing for hiring and firing with ease as well as by means of temporary contracts leading to higher staff turnover and (possibly) to low-trust labour relations.

Our econometric analysis seems to suggest that a greater internal flexibility is associated with a better ability to innovate. On the other hand, however, results on external flexibility are rather mixed. Especially for high-tech firms, a higher labour turnover negatively affects the percentage of new products in total sales. However, for low-tech firms there are some labour arrangements that positively affect the degree of firm innovativeness. A plausible explanation for these results is that an excessive use of flexible arrangements may be negative for firms' ability to innovate. In line with the European Directive 1999/70/EC, according to which 'permanent contracts must be the standard form across member States', the use of fixed-term contracts must be limited—due to technical, productive and organisational reasons—to extraordinary periods of firm activity. Unfortunately, we do not have detailed information on internal qualitative flexibility, which would really capture the adaptation of labour to the changing needs of the firm. We acknowledge that we are also unable to distinguish between different types of innovation (i.e. 'new to the market' or 'new to the firms'), which would probably provide clearer results for external flexibility. All these results combined, however, suggest that there is an optimal combination of flexibility, with respect to which an excessive use of labour flexibility can negatively affect the ability of a firm to innovate and, hence, survive and develop. An investigation of the economic impact of labour flexibility on the innovation activity of firms in the service sectors, which strongly emphasise the skills of their workers and organisational orientation to innovation, seems, therefore, an important area to investigate to further disentangle the complex links between labour flexibility and innovation.

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Appendix

Table A1 *The variables used in the econometric analysis*

Variable	Description
Share of innovative sales	Logit transformation of the share of turnover due to new products in 2000 or 2003. In 2000 the question was slightly different, as firms were asked what the share of turnover due to unchanged products was. Thus, the share of turnover for new products was derived as the complementary part for this period.
Innovation	Dummy variable that takes the value 1 if the enterprise reports to have introduced new production processes or products during 2001.
R&D expenditure	Average total expenditure for internal and external R&D divided per employee over the periods 2001–03 and 1998–2000.
Dummy R&D	Dummy variable that takes the value 1 if the firm reports to have carried out R&D during the periods 2001–03 and 1998–2000.
K investment	Average gross investments in innovative tangible goods per employee over the periods 2001–03 and 1998–2000.
Dummy investment	Dummy variable that takes the value 1 if the firm reports to have invested in innovative tangible goods during the periods 2001–03 and 1998–2000.
Age	Variable measuring firm age.
Young	Dummy equal to 1 if the firm is less than three years old.
Size	Average number of employees during the periods 2001–03 and 1998–2000.
M&As	Dummy variable that takes the value 1 if the firm has been involved in merger and acquisition dealings.
International competition	Dummy variable that takes the value 1 if the enterprise's most significant market is international (outside the EU).
Patents bought	Dummy that takes the value 1 if the firms bought patents during the periods 2001–03 and 1998–2000.
Patents sold	Dummy that takes the value 1 if the firms sold patents during the periods 2001–03 and 1998–2000.
International agreements	Dummy variable that takes the value 1 if the enterprise has developed technical agreements with firms operating on international markets (outside the EU).
Part-time permanent	Percentage of permanent part-time workers during the periods 2001–03 and 1998–2000.
Part-time temporary	Percentage of temporary part-time workers during the periods 2001–03 and 1998–2000.
Training	Percentage of workers who received training during the periods 2001–03 and 1998–2000.
Full-time temporary	Percentage of full-time temporary workers during the periods 2001–03 and 1998–2000.
Manpower	Percentage of workers coming from manpower agencies during the periods 2001–03 and 1998–2000.
Collaboration	Percentage of workers with collaboration contracts during the periods 2001–03 and 1998–2000.
Apprenticeship	Percentage of young workers hired with an apprenticeship contract during the periods 2001–03 and 1998–2000.
Turnover	Percentage of workers leaving and joining the firm during the periods 2001–03 and 1998–2000.
g_sales_{t-1}	Rate of sale growth calculated using variables as balance-sheet data during the periods 2001–03 and 1998–2000.