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“Work organisation, human capital and innovation strategies: new evidence from firm-level Italian data”

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ABSTRACT

By using firm-level data provided by the fourth round of the (Italian) Community Innovation Survey (CIS 2012), this paper explores whether the implementation of specific changes in work organisation within a firm influences its innovation performance, not only directly, but also *via* reinforcing the link between human capital resources and innovation. The authors also analyse the overall effect of human capital and work organisation, which enables them to identify which combination of these variables leads to the highest level of firms’ technological capabilities. Main findings confirm that not only the acquisition of new skills through the hiring of qualified personnel, but also how personnel management affects individual employees on the work floor should be considered to the development of firms’ innovation capacity: indeed, work organisation as well as strong positive complementarities or synergy effects between human capital and work organisation have been found to give firms a clear competitive advantage vis à vis both non-innovating firms and firms unable to internally generate new products and processes (i.e. entirely or at least partly by themselves). These positive effects are present and relevant in both manufacturing and service firms, whilst a more differentiated impact has emerged between firms in high-tech and low-tech sectors of the economy. On the whole, the contribution raises some relevant issues about the Italian lack of innovation in work organisation, which requires particular attention by the human resources management of firms and the industrial policy of governments.

Keywords: work organisation, human capital, technological capabilities, innovation generation, firms, industries

JEL codes: O30, O31, O32

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1. Introduction

Today, firms' economic success depends greatly on an effective ability to renew their internal knowledge base and competences in order to be able to move into activities less exposed to global competition, which implies the need to achieve specific *technological capabilities*, that is *dynamic* and *interactive* (Lundvall, 1992; Malerba, 1992; von Tunzellman & Wang, 2003, 2007). Within the evolutionary framework, these are meant as abilities "*to integrate, build and reconfigure internal and external resources/competences to address and shape rapidly changing business environments*" (Teece et al, 2007). The development of such capabilities by firms does not simply depend on R&D spending or capital formation, but stem from a strategy that integrates, builds and reconfigures both the *workplace organisation* and *competencies* in order to address changing environments by making the best use of the *creative and productive powers of employees* (Leoni, 2012). This leads to shift the focus of the analysis of innovation, beyond the pure technological domain, to the organisational dimension, which has been so far under-investigated (see Evangelista and Vezzani, 2010).

In this paper, we specifically put an emphasis on what is often called "*high-performance work practices*" (i.e. new human resources management policies entailing employees' responsibility and discretion in their work as well as skills use and upgrading) and its relation to the innovation performance of firms. Although most studies focus on the way *technological innovation* leads to *changes in the work organisation*, most recent research also emphasises the role of the latter for the purpose of improving the technological innovation performance of firms. This not only thanks to gains in terms of flexibility, but also because of increased opportunities for *workplace learning, skills upgrading* and *use of "creativity"* by individual workers. Indeed, these studies show that technological innovation often depends on employees' individual contribution and thus, indirectly, on organizational systems designed to provide a fertile environment for innovation, in particular by encouraging the *exploration* of new knowledge and different forms of *learning - learning by doing* (Arrow, 1962), *learning by using* (Rosenberg, 1982), *learning by interacting* (Lundvall, 1988) and *learning by searching* (Cohen and Levinthal, 1990). These factors, in turn, should favour the formation of *firm specific key technical competences*, as well as the creation of effective opportunities for individuals to express them through a *creative effort* in their work tasks (Lorenz and Valeyre, 2005; Arundel et al., 2007; Lorenz and Lundvall, 2010; Holm and Lorenz, 2015). Given this background, we agree that the mechanisms underlying the relationship between these "new" or "modern" work organisation practices and innovation are still misunderstood, calling for further research (see Laursen and Foss, 2003). In particular, we aim to examine whether "improving how jobs are performed" by individual employees have implications for firms' innovativeness, not only directly, but also *via* positively influencing the contribution of *human capital*. This in the beliefs that the kind of work organisation under study may create more or less room for employees' commitment and participation and thus for effective workplace learning and invention, so that its implementation might be more beneficial in some contexts than in others.

To the best of our knowledge, available empirical evidence from microeconomic literature on these issues is scarce. Indeed, previous research which provides robust evidence for a positive and significant impact of human capital on innovation (Soboleva, 2010) has hardly considered how personnel management affects individual employees on the work floor. In this respect, the common-sense opinion remains that R&D departments and high-tech firms constitute the main source of innovation. Conversely, this research builds on previous studies showing that, if properly supported, front-line employees effectively develop and produce new products, processes and services, called "employee-driven innovation"; this is crucial for firms in medium-low and low-tech industries, with limited or no independent R&D capacities, where

innovation most likely depends on other activities and behaviours, such as design, training or the use of advanced machinery and tools (Santamaria et al., 2009). Hence, using firm-level data provided by the Italian Community Innovation Survey (CIS 2012), we provide a contribution in this direction by answering to the following questions.:

-how do work organisation and human capital within firms relate to each other, i.e. are they complementary or substitutes?

-does work organisation have implications for the contribution of human capital to innovation?

-what is the overall effect of work organisation and human capital on the innovative performance of firms?

-are there systematic differences between industries -i.e. manufacturing vs services and high-techs vs low-techs - in all these respects?

For the scope of this study, Italy is an interesting case for at least two main reasons. First, because this country has been so far particularly reticent in innovating in its own work organisation. A survey carried out by Eurofound (2011) draws attention to this issue by showing that, in 51% of cases, Italy adopts none of the workplace organisational innovations under study, in 32% at least one, and only in 17% of cases at least two. Second, because of the Italian gap in both educational achievement and innovation activity. As far as the former is concerned, the available empirical evidence shows that Italy displays the lowest share of graduates amongst all major European countries: less than one fifth of workers holds a college degree, against almost one third in the Euro Area. Moreover, the Italian labor market is characterized by higher recruitment costs of skilled workers: a 1% increase of the labor supply reduces the associate recruiting cost by around 2% against 1% in Spain and 0.2% in France and Germany (Colonna, 2014). As for the latter, it is well known that the Italian system exhibits a bias toward sectors with a relatively low rate of innovation and labor productivity. According to Pini (2013), the overall lower productivity of Italian firms can be explained not only by a lower level of private investments in technology (physical capital in particular), but also by a lower capacity to translate these investments into productivity gains: although almost not considered in economic research, this can be ascribed to a lack of innovations in work organisation. In line with this, in this paper we aim at putting forward an original perspective, such that work organisation may be crucial for firms to the extent that it makes also the simple hiring of qualified personnel more fruitful. Hence, if the link between human capital and firms performance is stronger for firms which have implemented complementary changes in work organisation, we would thus find an additional argument in favour of industrial and innovation policies aimed at incentivising the diffusion of such practices among firms.

An important issue in the present setup refers to finding an appropriate measure of the innovation performance of firms. In most previous works, this is measured by R&D intensity, higher probability of introducing an innovation, higher count of new products/processes and patents introduced, higher degree of innovativeness (i.e. radical versus incremental), sales and profit growth. In this work, in addition to incorporating the aforementioned "organisational effects", we examine a new measure of firms' innovativeness. In particular, given the data at our disposal, we start by defining *technological innovation* as the simple introduction of new products and/or processes by a firm and considering the complete sample of firms, which allows us to distinguish between innovators and non-innovators. In a second step, building on previous research (Divella, 2016), we focus on the sub-sample of

innovative firms and differentiate between various levels of firms' technological capabilities. In this respect, a shortcoming of most previous studies on innovation is that they limit the analysis to the first step, namely to the factors influencing the innovative choice of firms, which can be misleading as long as it leads to consider all the innovating firms on the same footing.

The rest of the paper is organized as follows. In the following section we discuss more in detail the theoretical background and hypotheses of the research. Section three provides an overview of the data and explains the econometric strategy. Section four summarises the main empirical results, whilst some concluding remarks and implications for policy are offered in the last section.

2.Literature background and hypotheses

In this paper, we focus on a specific dimension of work organisation within firms, which comprises both the opportunities workers may have to develop the (technical) skills required in their job through *training* and the *autonomy* given to the workers in order to apply them. These (and other) factors are often summarised with the acronym HPWO (High Performance Work Organisation), which indicates a new firm configuration outside the Taylor-Fordist tradition based on a strong centralisation of decision authority and narrowly defined occupations (see Foss, Laursen and Pedersen, 2011; Leoni, 2012).

There are two complementary literatures which address the relation between these new work organisational practices and the technological innovation performance of firms. A first one is the "*high performance work system*" literature, which deals with the diffusion of the Japanese-style organisational practices in the US and Europe (see Laursen and Foss, 2012 for a review): developed by large Japanese automobile and electronics firms in the 1970s and 1980s, many of them were innovations expected to enhance the firms' capacity to innovate by increasing employee involvement in problem solving and operational decision-making, such as teams, problem-solving groups and employee responsibility for quality control. The diffusion of such practices and arrangements is thus seen as having contributed to the progressive transformation of more hierarchically structured firms into more flexible or "transformed" organisations. A second body of literature is the "*organisational design*" literature that has tended to develop more complex taxonomies (Mintzberg, 1979, 1983; Lam, 2005; Lam and Lundvall, 2006). On the whole, these studies have contributed to shed light on how factors that hamper innovation might not always be insufficient resources allocated upstream to R&D activities (i.e. fundamental competences to generate as well as to absorb, accumulate and exploit technological knowledge) or a lack of external integration (i.e. fundamental opportunities for external knowledge sourcing through networking and cooperation); rather they can be located down-stream and result from rigid organisational frameworks providing limited incentives for employees to take part in and effectively contribute to the innovation process.

The theory suggests multiple mechanisms through which the implementation of a HPWO may be favourable to the innovative capacity of firms. Lam (2005), for instance, contrasts two ideal organisational forms that support different styles of learning and innovation: on the one hand, the "*operating adhocracy*" characterised by high levels of discretion in work, which provides scope for *exploring* new knowledge and consequently leads to a superior capacity for *radical innovation*; on the other, the "*j-form*", which is relatively more bureaucratic, relying on formal team structures and rules of job rotation, typically adopted by firms that excel at *incremental innovation*. In line with this, Arundel et al. (2007) have shown that, in countries where work is organised to support high levels of discretion in solving complex problems, firms tend to be

more active in terms of *endogenous innovation*, notably innovation developed (at least to some extent) in house; by contrast, in countries where learning and problem-solving on the job are more constrained and little discretion is left to the employee, firms tend to engage in a supplier-dominated innovation strategy, which means that their technological renewal mostly reflects *absorption of innovations* developed elsewhere. In the management literature, there has also been a focus on how *creativity* emerges from the interaction between the individual employee and various aspects of management style and work organisation (Amabile et al, 1996; Woodman, Sawyer and Griffin, 1993). Drawing inspiration from this literature, as well as from Florida's research focusing on the relation between human capital investments, creativity and regional economic performance (Florida, 2002; Florida, Mellander, and Stolarick, 2007; Mellander and Florida, 2006), Lorenz and Lundvall (2010) have provided the first map of creativity at work for 27 members of the European Union: by taking into account differences in the institutional context and industrial structure across nations, their analysis confirms that creative jobs are more likely at workplaces where managers support employees and where work is organised to promote knowledge diversity.

In order to add to this literature and put forward knowledge about this topic, this paper aims at examining whether (and to what extent) the changes in work organisation under study influence firms' innovativeness, not only directly, but also via reinforcing the link between human capital and innovation. From an organisational perspective, human capital is the result of a firm's deliberate investment through the selective hiring of employees with high general skills or formal education. Firms can thus use selection to increase the level of the generic and academic knowledge of the individuals working in the organisation, while focusing on work organisation in order to take maximum advantage of their human capital investments, notably to deploy the employed human resources effectively: this could involve providing on-job training activities aimed at developing more firm-specific technical skills (Groot and Van Den Brink, 2000; Skaggs and Youndt, 2004) as well as allowing workers to use their own ideas as well as to apply their (both generic and technical) skills in work. First, this implies that HPWO practices should be expected to work well when adopted, not singly, but as a system of mutually reinforcing practices: on the one hand, the innovation pay-off from giving shop floor employees more problem-solving rights likely depends on the level of training of such employees; on the other, employees may invest more in upgrading their skills if they are also given extensive problem-solving rights, especially if they are provided with intrinsic or extrinsic motivational encouragements (Laursen and Foss, 2003). Second, the effect of HPWO practices can be expected to be complementary with other firm-level variables, notably the share of highly educated workers. Indeed, generic human capital (i.e. educated labour) *per se* is important as higher education can impact on innovation in two ways: firstly, graduates can *invent* and develop new technologies and, secondly, they can *exploit* technological progress (Lundvall and Johnson, 1994). However, high levels of formal education do not necessarily translate into high levels of up-to-date productive skills, so that further investments in education will not lead to necessary improvements in the firm's demonstrated ability to innovate, unless coupled with on-job training activities. This latter provides fundamental opportunities to expand the knowledge base of all employees, making them better able to perform their job through *on-going learning* (Appelbaum et al., 2000), which could be particularly useful, for instance, to adapt the skills and knowledge of more mature workers to the requirements of the current changes in products and technology (Arundel et al, 2007). Hence, on the one hand, the effect of training activities is likely to be higher in firms with higher endowments of educated workers, since people who have received better education generally have a higher potential to learn and develop a greater knowledge (Hatch and Dyer, 2004; Hitt et al., 2001; Rauch et al., 2005) as well as to adapt more rapidly and efficiently to

the new tasks (Blundell et al., 1999). On the other, firms may also use job training as substitute for formal education, namely to make up for limited investments in high qualified personnel, which implies that positive synergies between these two items cannot be taken for granted. Likewise, more discretion and responsibility left at the bottom, although relevant as key drivers of work motivation and employees commitment to the organisation (Arundel et al. 2007), might be not effective with respect to enhancing firms' innovation capacity where the level of workers' basic knowledge and technical skills does not allow them to give an effective contribution in this direction.

Of course, in addressing these issues, relevant differences in the technological dynamism of the various sectors of the economy must be taken into account, that is the industrial structure. Organisational theory suggests that more knowledge intensive production activities may involve higher degrees of strategic uncertainty for firms and performance ambiguity in relation to individual employees. Therefore, human resource management practices should perform better within knowledge intensive industries as compared to other industries of the economy (see Laursen, 2012). In line with this, Laursen 2002 has found the application of complementary work organisation practices to be more effective in high and medium high-tech sectors. Since investment in human capital is also more critical in fast-paced, technology based industries, we can expect strategies based on the hiring of a highly skilled workforce combined with work organisational changes aimed at making the best of such investments to be more effective for firms in high-tech sectors. The opposite is true for firms operating in slower moving industries and marketplaces with less change, where it may become feasible to take the long approach and develop the necessary skills within the firm, which implies that work organisation in these sectors (especially on-job training of personnel) is likely to be more relevant than a higher share of highly educated workers.

In addition, finding an appropriate and effective measure of firms' technological capabilities is not an easy task. R&D expenditures and the number of patents applied for or granted are the most frequently used indicators, though their weaknesses are well known (see Capriati, 2013). Previous works relying on the evolutionary framework (Iammarino et al., 2012; Barbieri et al., 2013) have argued that in order to evaluate firms' innovation capacity, variables related to outcomes, such as the introduction of new products and processes should be more appropriate. We agree with this view, but we believe that this indicator may turn out to be misleading since it leads to consider all the innovating firms on the same footing. Rather, within the evolutionary framework, firms are supposed to achieve different levels of technological capabilities as long as they confront a range of different circumstances, resources and opportunities for exploring new knowledge, learning and innovating (von Tunzelmann and Wang 2007). Therefore, building on previous research (Divella, 2016), we agree that a better way to capture and differentiate between various levels of firms' capabilities is to put them in relation to the way innovation has been actually performed. Indeed, most innovations result from the *adoption* or *imitation* of what others have already developed, rather than from real *invention*, that is by *internally generating* new knowledge and ideas (Damanpour and Wischnevsky, 2006). In this respect, a major drawback of measures like R&D and patents, but also of the simple introduction of new products and processes by the firms, is that they completely fail to capture innovation that occurs through processes of diffusion, such as when firms innovate by modifying and adapting technology already developed by other firms or institutions (imitation) or when firms do not develop innovations in-house, but all innovations are acquired from external sources (adoption), as in the case of the purchase of machinery embedded new technologies. Therefore, confusion arises when the launches of new technologies by firms are considered on the same footing, as the nature of the two possible underlying processes is profoundly different: the internal

generation of innovations, since it requires the creation and application of new knowledge and ideas, is more likely to involve *exploratory processes and alliances* characterized by high variation, search, discovery, experimentation, uncertainty, risk and failure; firms that instead innovate by *imitation and adoption* can mostly rely on *exploitation* of existing knowledge, observe the behaviour of other agents in the market dealing with similar technologies and possibly imitating it (see Lavie, Stettner & Tushman, 2010, for a review). Given this “dual nature” of innovation activity, firms able to generate innovations (at least partially) internally should have higher technological capabilities than those who innovate by imitation or adoption of technologies originally developed elsewhere (Arundel, 2007; Huang, Arundel & Hollanders, 2010).

Hypothesis 1: the implementation of HPWO practices (On-job training & Work changes aimed at the empowerment of employees in doing their job) within firms complement, rather than substitute, human capital (i.e. hiring of educated labour);

Hypothesis 2: HPWO positively moderates the contribution of human capital to innovation, which means that firms combining human capital with the adoption of HPWO practices are more likely to be innovative, i.e. able to introduce at least one new product and/or process;

Hypothesis 3: innovative firms combining HPWO practices with human capital are also more innovative than their competitors, i.e. able to generate innovations (at least in part) by themselves instead of merely relying on imitation and adoption of innovations already developed by others;

Hypothesis 4: the combined effect of HPWO practices and human capital is more likely to be effective in high-tech compared to low-tech sectors; HPWO practices *per se* are, instead, more conducive to innovation performance in low-tech compared to high-tech sectors.

3. Econometric analysis

3.1 Data and construct

This work uses data from the Italian Community Innovation Survey (CIS 2012) provided by ISTAT, which is part of the wider Community Innovation Survey covering European countries and refers to the three year-period 2010-2012. The dataset provides detailed firm-level information on innovation behaviour understood from a broad perspective and is drawn on firms’ responses to a postal questionnaire developed by the European Commission (Eurostat) and Member States, under the guiding principles of the Oslo Innovation Manual (OECD, 2005). The postal questionnaire has been addressed to more than 163 thousands Italian firms with 10 or more employees and has a wide sectorial coverage, including both manufacturing and services. Valid responses received from 18697 firms constitute the final representative sample.

Dependent variables

Following the theoretical framework widely discussed, first we define **Technological innovation** as the introduction of new products and/or processes by a firm and, by considering the complete sample of firms, we distinguish between *innovators* (*Technological innovation* = 1) and *non-innovators* (*Technological innovation* = 0). Then, we focus on the sub-sample of innovative firms and distinguish between different levels of firms’ technological capabilities according to the way innovation has been performed. Note that, for each firm, the Italian CIS asks information on the way the product and process innovations introduced during the reference period have been developed, allowing multiple choices between four options:

- 1) *your enterprise by itself*;
- 2) *your enterprise together with other enterprises or institutions*;
- 3) *your enterprise by adapting or modifying goods, services or processes originally developed by other enterprises or institutions*;
- 4) *other enterprises or institutions*.

Drawing on firms' answers to these questions, four binary dependent variables have been created. We consider that innovation generation occurs as soon as the firm declares that its new products and/or processes have been developed by "*your enterprise by itself*" (**Generation in-house**) or by "*your enterprise together with other enterprises or institutions*", which means at least partially by the firm (**Generation in cooperation**); innovation **Imitation** is done by firms whose new products and/or processes have been developed "*by adapting or modifying goods, services or processes originally developed by other enterprises or institutions*"; whereas **Adoption** happens when firms introduce new products and/or processes developed by "*other enterprises or institutions*".

Not surprisingly, given that it is unlikely that any firm only generates or adopts innovations, these four binary indicators turn out to be highly correlated. Moreover, it is worth to bear in mind that, for the purposes of this paper, we consider all the innovating firms (i.e. able to introduce new products and/or processes) as firms with technological capabilities, but we classify as firms with higher innovation capacity those firms that have been able to introduce new products and/or processes developed (at least to some extent) by internal generation processes, notably by Generation in-house (i.e. entirely by themselves) or by Generation in cooperation (i.e. at least in part by themselves) compared with Imitation and Adoption: indeed, we aim at assessing the *creative effort* that firms expend on their internal innovation activities and how it can be fostered by individual employees' work.

Independent variables

The Italian CIS also detects whether the firms have implemented "*new methods of organising work responsibilities and decision making (i.e. first use of a new system of employee responsibilities, team work, decentralisation, integration or de-integration of departments, education/training systems, etc.)*", which we consider as a general indicator of the adoption of work organisational changes by firms aimed at giving more autonomy or discretion to the workers in their job tasks (**Work changes**). Other important questions in the CIS ask firms to indicate whether they have provided "*in-house or contracted out training for your personnel specifically for the development and/or introduction of new or significantly improved products and processes*", here used as proxy of firm specific technical skills acquired through on-job training activities (**On-job training**); and the portion (on a 0-1-2-3-4-5-6 scale, 0=0%, 1=1-4%, 2=5-9%, 3=10-24%, 4=25-49%, 5=50-74%, 6=75-100%) of employees educated to the degree level, which we use to construct our binary indicator of the firm's **Human capital** endowment: it is equal to 1 if the share of highly educated employees within a firm is at least 10% or higher (namely, above the corresponding mean value).

By combining information provided by this set of questions, we consider the implementation of High-performance work organisation (**HPWO**) practices by firms by assessing the cumulative effects of On-job training and Work changes (dummy variable equal to 1 if both conditions are simultaneously present). Moreover, we construct four dichotomous variables in order to account for possible combinations of **HPWO** practices and **Human capital** endowment within a firm:

- **High_High** stands for "High" human capital and "High" performance work

organisation, which means that it equals to 1 if the share of highly educated employees is above the average (Human capital=1) and the firm has also adopted high-performance work organisation methods (HPWO=1);

- **Low_High** detects firms with Human capital=0 and HPWO=1
- **High_Low** is, instead, equal to 1 when Human capital=1 but HPWO=0
- **Low_Low** finally accounts for firms with Human capital=0 and HPWO=0

Control variables

Besides the key independent variables described, we include other important regressors to account for firms' external knowledge sourcing activities and their absorptive capacity:

- **Openness** measures the extent to which firms draw intensively from different search channels or sources of innovative ideas outside any formal cooperation agreement; it is based on the question of the CIS asking firms to rate the importance of 11 different sources of knowledge or information for innovation (hence not necessarily implying formal cooperation), ranging from "not used" to "highly important"; following the method used by Laursen and Salter (2006), we construct this as a categorical indicator taking values from 0 (no external sources used to high or medium degree) to 11 (all types of different external knowledge sources used to high or medium degree)¹;
- **External cooperation** is a dummy variable which equals to one if a firm has cooperated with at least two different external partners and/or at two or more different geographical locations on R&D and other innovation activities; this is aimed at capturing the effects of heterogeneity of collaboration (both in terms of partners and geographical locations involved) and thus potential synergy effects arising from the use of different cooperation strategies²;
- **Intra-mural R&D**, which should better account for the firms' absorptive capacity, is measured by a categorical indicator that equals to 0 when the firm has not invested in internal R&D, or equals to 1 if the firm has invested in internal R&D only occasionally (i.e. as needed), or equals to 2 if the firm has invested in internal R&D continuously (which should better account for the presence of firms' internal R&D departments)³;
- **Other innovation activities** accounts for the total number of innovation related activities (different from internal R&D) carried out by a firm, from 0 to 6; these specifically include: extra-mural R&D (contracted out to other firms or research institutions); acquisition of machinery and equipment; acquisition of existing knowledge from other enterprises or organisations; market introduction of innovations; design and other activities, such as feasibility studies, testing, tooling up, industrial engineering etc.

Two further variables account for market characteristics:

- **Market size** reflects the overall dimension of the market of interest; we construct this indicator as the sum of four binary variables accounting for the geographic market

where the firm operates and competes, that is: 1)local or regional, 2)national, 3)international within the EU and 4)international outside the EU;

- **Lack of demand** aims at capturing the lack of demand-pull mechanisms, by measuring the importance attached by firms (on a 0-1-2-3 scale) to the lack of demand for innovative products as an obstacle to innovate (0=not relevant; 1=low; 2=medium; 3=high).

Finally, two variables related to firms' characteristics routinely used in empirical studies on innovation have been included, such as: **Firm size** (the log number of a firm's employees) and **Group** (whether a firm is part of a corporate group). We also add industry dummies to account for different technological opportunities available to firms in their sector. The clustering criteria, in this case, follows the OECD classification of manufacturing industries into categories based on technology (OECD, 2011), that has helped to create the following typology: 1)**Industry high-tech**; 2)**Industry medium high-tech**; 3)**Industry medium low-tech**; 4)**Industry low-tech**; 5)**Knowledge intensive business services (KIBS)**; 6)**Other services**; 7)**Construction, retail&distribution**.

3.2 Estimation strategy

We start by considering the complete sample of firms, both innovators and non-innovators. By the means of a probabilistic regression, we estimate the relationship between *Technological innovation* (a dichotomous variable that takes value 1 if a firm *i* is innovative, notably has introduced a product and/or a process innovation during the reference period, 0 otherwise) and the following variables: HPWO, Work changes and On-job training (taken separately), Human capital. In order to assess the moderating role of work organisation with respect to human capital, we also include interactions between these variables.

Therefore, the model we estimate is as follows:

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* > 0 \text{ , the firm is innovative} \\ 0 & \text{if } Y_i^* \leq 0 \text{ , otherwise} \end{cases}$$

Y_i^* being the latent variable defined as

$$Y_i^* = \beta_0 + X' \beta_1 + \varepsilon$$

where X is the vector of the described covariates and ε the error terms.

In a second step, we restrict the analysis to firms actually able to introduce at least one new product or process during the three-year period 2010-2012 (i.e. 6371 units specifically considered as "innovative" for the scope of this study)⁴. This in order to assess the effect of different combinations of HPWO and Human capital on the probability that firms will achieve higher levels of technological capabilities as measured by their capacity of generating innovations, in-house or in cooperation (thus at least partly by themselves), rather than by imitation or adoption strategies (which indeed implies that they have been originally developed by others). As for the estimation, in this case, we adopt a multivariate probit model

in order to account for the fact that different innovation strategies can occur simultaneously (recall, on this, that firms' answers to the set of CIS questions about how the product and process innovations introduced have been developed are not mutually exclusive). This method is the most appropriate for this analysis, since it allows to predict several correlated binary outcomes jointly and to control for potential correlation of the error terms. Indeed, the four dependent variables considered are highly correlated; moreover, it is plausible that effects of unobserved characteristics (thus included in the error terms) are correlated across alternatives, in a way that each error term can be thought as divided into two parts, one specific for each equation describing the outcome of interest and one common to the others:

$$\varepsilon_1 = \eta + u_1 ;$$

$$\varepsilon_2 = \eta + u_2 ;$$

$$\varepsilon_3 = \eta + u_3 ;$$

$$\varepsilon_4 = \eta + u_4 .$$

[The basic formulation for a quadrivariate probit model is as follows⁵:

$$y_{i1}^* = x_{i1}'\beta_1 + \varepsilon_{i1} , \quad y_{i1}=1 \text{ if } y_{i1}^* > 0, 0 \text{ otherwise ;}$$

$$y_{i2}^* = x_{i2}'\beta_2 + \varepsilon_{i2} , \quad y_{i2}=1 \text{ if } y_{i2}^* > 0, 0 \text{ otherwise ;}$$

$$y_{i3}^* = x_{i3}'\beta_3 + \varepsilon_{i3} , \quad y_{i3}=1 \text{ if } y_{i3}^* > 0, 0 \text{ otherwise ;}$$

$$y_{i4}^* = x_{i4}'\beta_4 + \varepsilon_{i4} , \quad y_{i4}=1 \text{ if } y_{i4}^* > 0, 0 \text{ otherwise ;}$$

$$E(\varepsilon_{i1} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = E(\varepsilon_{i2} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = E(\varepsilon_{i3} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = E(\varepsilon_{i4} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = 0 ;$$

$$\text{Var}(\varepsilon_{i1} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = \text{Var}(\varepsilon_{i2} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = \text{Var}(\varepsilon_{i3} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = \text{Var}(\varepsilon_{i4} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = 1;$$

$$\text{Cov}(\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}, \varepsilon_{i4} | x_{i1}, x_{i2}, x_{i3}, x_{i4}) = \rho ;$$

$$i = 1, 2, 3, \dots n .]$$

Finally, we replicate the analysis by taking into account high-tech (Industry high-tech, Industry medium high-tech and KIBS) and low-tech sectors (Industry low-tech, Industry medium-low tech, Other services and Construction, retail and distribution) separately: this in order to investigate whether different combination of Human capital and HPWO practices have different effects across different groups of industries.

From the methodological point of view, it must be mentioned that any conclusion regarding causality is clearly limited by the cross-sectional nature of the data, which may suggest reverse causation for some of the explanatory variables employed, in particular those referred to changes in the work organisation of firms as these are sometimes, but not always, linked to technological change⁶. Another potential issue in the present set-up specifically refers to the multivariate probit estimates, as these are exposed to the well-known "selection bias" (Heckman, 1979): whilst our first step estimation (probit model) allows us to include all the firms present in the CIS sample, in this case the potential bias related to the sample selection problem arises because the dependent variables of interest (referred to the way innovation has been performed) are only observed for a non-randomly restricted sample, that is only for firms that have introduced a product or a process innovation.

These are both typical econometrics issues arising when CIS data are drawn from one single

wave and used for estimating the innovation performance of firms (see also Evangelista and Vezzani, 2010). As far as the former is concerned, given the weaknesses of the instruments at our disposal, we do not make any attempt to use an instrumental variable approach in order to tackle the potential endogeneity bias. However, we believe that the study design, though it does not allow to shed light on the actual direction of causality and thus to capture short term cause-effects relationships, is appropriate to detect structural associations between variables (different combinations of HPWO and Human capital on the one hand and different innovation modes on the other) and, thus, persistent differences in the technological capabilities of firms which, in turn, could explain differences in their long term economic performances. Of course, considering the readily availability of data from successive waves of the CIS, a more detailed analysis of these issues using firm panel data would constitute a useful angle for further research. Nevertheless, many national CIS actually provide few opportunities for such analysis, as linking individual survey waves often results in a small and unrepresentative sample with strong focus on large firms. As for the latter, in order to tackle the possible selectivity issue, regressions on the full sample of firms have also been run applying the Heckman correction procedure, which has shown consistent results (see Appendix for details).

3.3 Descriptive statistics

The following tables report the list of the variables employed for this analysis with a detailed description (Table 1), the distribution of firms and their technological capabilities across industries (Tables 2) and the relevance of HPWO practices and Human capital (with their possible combinations) across innovative firms in each industry (Table 3).

Table 1. Indicators used in the econometric analysis

Name	Type	Description
<i>Controls</i>		
Firms size	Continuous	number of firms employees (in logarithm)
Group	Dummy	whether a firm is part of an enterprise group
Intra-mural R&D	Categorical	overall intensity (on a 0 - 1 - 2 scale) of intra-mural R&D (0= no internal R&D; 1= internal R&D occasionally; 2= internal R&D permanently)
Other innovation investments	Categorical	overall number (from a 0 to 6) of the other innovation activities (different from intra-mural R&D) carried out by a firm
Openness	Categorical	total number (from 0 to 11) of different external sources of knowledge used from medium to high degree by a firm
External cooperation	Dummy	whether a firm cooperates for innovation with at least two different partners and/or at two or more different geographical locations
Market size	Categorical	overall dimension of the market of interest (1=local/regional; 2=national, outside the home region; 3=international, within EU; 4=international, outside EU)
Lack of demand	Dummy	percieved lack of demand as obstacle to innovation activities carried out by a firm, from 0 to 4 (0=not relevant; 1=low; 2=medium; 3=high)
Industry high-tech	Dummy	whether a firm is in high-tech industry
Industry medium high-tech	Dummy	whether a firm is in medium high-tech industry
KIBS	Dummy	whether a firm is in knowledge intensive services
Industry low-tech	Dummy	whether a firm is in low-tech industry
Industry medium-low tech	Dummy	whether a firm is in medium low-tech industry
Other services	Dummy	whether a firm is in other services (different from KIBS)
Construction, retail&distribution	Dummy	whether a firm is in construction, retail or distribution

Table 2. Distribution of technological capabilities across industries

	High-tech industry	Medium high-tech industry	KIBS	Low-tech industry	Medium-low tech industry	Other services	Construction, retail & distribution	Total
All firms in the sample	203 (1.1)	953 (5.1)	2078 (11.1)	2020 (10.8)	1151 (6.2)	2548 (13.6)	9744 (52.1)	18697 (100.0)
<i>Dependent variables</i>								
Technological Innovation	157 (2.5)	646 (10.1)	991 (15.6)	965 (15.1)	537 (8.4)	823 (12.9)	2252 (35.3)	6371 (100.0)
Generation in-house	135 (2.1)	587 (9.2)	764 (12.0)	795 (12.5)	448 (7.0)	575 (9.0)	1634 (25.6)	4938 (77.5)
Generation in cooperation	102 (1.6)	344 (5.4)	598 (9.4)	448 (7.0)	244 (3.8)	406 (6.4)	994 (15.6)	3136 (49.2)
Imitation	33 (0.5)	103 (1.6)	242 (3.8)	158 (2.5)	87 (1.4)	173 (2.7)	420 (6.6)	1216 (19.1)
Adoption	18 (0.3)	54 (0.8)	159 (2.5)	93 (1.5)	43 (0.7)	103 (1.6)	390 (6.1)	860 (13.5)

Values refer to the number of firms (relative percentages in brackets)

Table 3. Relevance of HPWO and human capital across innovative firms in each industry

	High-tech industry	Medium high-tech industry	KIBS	Low-tech industry	Medium-low tech industry	Other services	Construction, retail & distribution	Total
HPWO	63 (1.0)	169 (2.7)	369 (5.8)	205 (3.2)	120 (1.9)	212 (3.3)	533 (8.4)	1671 (26.2)
Work changes	98 (1.5)	327 (5.1)	641 (10.1)	421 (6.6)	240 (3.8)	439 (6.9)	1175 (18.4)	3341 (52.4)
On-job training	94 (1.5)	277 (4.3)	516 (8.1)	349 (5.5)	200 (3.1)	337 (5.3)	899 (14.1)	2672 (41.9)
Human capital	133 (2.1)	343 (5.4)	836 (13.1)	292 (4.6)	162 (2.5)	348 (5.5)	695 (10.9)	2809 (44.1)
High_High	52 (0.8)	110 (1.7)	336 (5.3)	75 (1.2)	45 (0.7)	116 (1.8)	188 (3.0)	922 (14.5)
High_Low	23 (0.4)	85 (1.3)	153 (2.4)	105 (1.6)	49 (0.8)	87 (1.4)	185 (2.9)	687 (10.8)
Low_High	11 (0.2)	59 (0.9)	33 (0.5)	130 (2.0)	75 (1.2)	96 (1.5)	345 (5.4)	749 (11.8)
Low_Low	5 (0.1)	126 (2.0)	50 (0.8)	295 (4.6)	168 (2.6)	172 (2.7)	526 (8.3)	1342 (21.1)

Values refer to the number of firms (relative percentages in brackets); all statistics are here computed on the sub-sample of innovative firms.

As can be seen (Table 2), the overall sample of firms is dominated by the low-tech sectors of the economy, while firms in high-techs (High and Medium-high tech industry and KIBS) are relatively scarce, which is in line with the distribution of the Italian industrial system (ISTAT, 2011). The majority of firms operate in Construction, retail and distribution, whereas KIBS is the most numerous category among the high-techs. Only a minority of firms in the sample is innovative (i.e. able to introduce at least one new product or process during the reference period), that is 34,1% corresponding to 6371 units. However, about 78% of the innovating firms have been able to generate new products and processes entirely in-house.

Turning to Table 3, it is interesting to note that more than 52% of the innovative firms have implemented the Work changes under study and also that almost 42% of those firms have invested in On-job training; nevertheless, only a tiny share of innovative firms have implanted strategies encompassing both factors (HPWO), notably 26,2%, which decreases to 14,5% if we consider also complementary Human capital investments (High_High). Firms successfully combining HPWO and Human capital are mostly in KIBS.

4.Results

The following tables present the results of the regression analysis carried out for our two firm performance indicators: the simple introduction of product and/or process innovations (Table 4); the difference across “innovators” in terms of how they perform innovation (Table 5). The first estimation has been carried out on the whole sample of firms, whilst the second on the targeted sample of innovative firms⁷.

Table 4. Probit regressions (full sample)

Explanatory Variables	Dependent variable: <i>Technological innovation</i>			
	I	II	III	IV
<i>Firm size</i>	0.0360 (0.0271)	0.0340 (0.0272)	0.0310 (0.0273)	0.0280 (0.0274)
<i>Group</i>	-0.0348 (0.0591)	-0.0315 (0.0588)	-0.0317 (0.0596)	-0.0256 (0.0593)
<i>Intra-mural R&D</i>	-0.0829** (0.0377)	-0.0812** (0.0377)	-0.0871** (0.0379)	-0.0861** (0.0380)
<i>Other innovation investments</i>	0.1082*** (0.0273)	0.1072*** (0.0272)	0.1014*** (0.0281)	0.0975*** (0.0281)
<i>Openness</i>	0.0144 (0.0135)	0.0144 (0.0136)	0.0102 (0.0134)	0.0101 (0.0134)
<i>External cooperation</i>	0.0510 (0.0926)	0.0498 (0.0928)	0.0511 (0.0928)	0.0416 (0.0932)
<i>HPWO (Work changes & On-job training)</i>	0.3259*** (0.0776)	0.2486*** (0.0946)		
<i>Work changes</i>			0.2788*** (0.0547)	0.3100*** (0.0681)
<i>On-job training</i>			0.1610*** (0.0618)	0.0630 (0.0727)
<i>Human capital</i>	0.1426** (0.0603)	0.1130* (0.0637)	0.1310** (0.0608)	0.0785 (0.0814)
<i>Human capital X HPWO</i>		0.5685*** (0.1265)		
<i>Human capital X On-job training</i>				0.2844** (0.1211)
<i>Human capital X Work changes</i>				-0.0754 (0.1130)
<i>Market size</i>	0.1094*** (0.0262)	0.1100*** (0.0262)	0.1103*** (0.0262)	0.1116*** (0.0263)
<i>Lack of demand</i>	0.0392 (0.0269)	0.0395 (0.0269)	0.0387 (0.0269)	0.0393 (0.0270)
<i>Industry high-tech</i>	-0.0031 (0.1919)	-0.0125 (0.1928)	-0.0011 (0.1933)	-0.0187 (0.1950)
<i>Industry medium high-tech</i>	0.1441 (0.1092)	0.1439 (0.1091)	0.1660 (0.1098)	0.1647 (0.1099)
<i>KIBS</i>	0.2306** (0.0905)	0.2225** (0.0907)	0.2275** (0.0910)	0.2187** (0.0917)
<i>Industry low-tech</i>	0.2791*** (0.0903)	0.2801*** (0.0900)	0.3091*** (0.0910)	0.3095*** (0.0908)
<i>Industry medium low-tech</i>	0.1443 (0.1036)	0.1406 (0.1033)	0.1681 (0.1051)	0.1653 (0.1049)
<i>Other services</i>	0.3011*** (0.0893)	0.3001*** (0.0894)	0.3120*** (0.0899)	0.3145*** (0.0900)
<i>Construction, retail&distribution</i>	omitted	omitted	omitted	omitted
<i>Constant</i>	0.7311*** (0.1085)	0.7457*** (0.1098)	0.6491*** (0.1097)	0.6763*** (0.1133)
	Pseudo R2= 0.0529	Pseudo R2= 0.0536	Pseudo R2= 0.0588	Pseudo R2= 0.0608
	Wald chi2(16)= 127.95***	Wald chi2(17)= 126.78***	Wald chi2(17)= 146.82***	Wald chi2(19)= 150.82***
	Log pseudolikelihood= -1335.6431	Log pseudolikelihood= -1334.7386	Log pseudolikelihood= -1327.3578	Log pseudolikelihood= -1324.5004
	Number of obs.= 6733	Number of obs.= 6733	Number of obs.= 6733	Number of obs.= 6733

*p<0.10; **p<0.05; ***p<0.01 (two-tailed); robust standard errors in brackets.

Starting from Table 4, we estimate several specifications. In column I, we observe that HPWO and Human capital turn out to be both positive and significant as expected (at 5% and 1% level, respectively); these results are confirmed when the variable HPWO is disaggregated in order to assess the separate role of its two components (column III), Work changes and On-job training, which are indeed both positive and statistically significant (at 1% level of confidence). Consistently with Hypothesis 1, the positive signs of all the estimated coefficients support the complementary nature of such practices: firms combining the hiring of high qualified personnel with on-job training activities directed to develop firm-specific technical skills and organisational changes directed to boost employees' responsibility and decision making in their work tasks, are more likely to introduce new products and processes. This result is further supported by the existence of significant differences in the effect of Human capital between firms which have implemented complementary changes in work organisation and firms which have not (Hypothesis 2): indeed, Human capital in the second specification gains considerably in significance when interacted with HPWO. This finding proves that the simple hiring of graduated workers (without organisation) is likely to play only a limited role; on the contrary, HPWO practices, besides having a relevant role *per se*, may have a greater (indirect) impact on firms' innovativeness where workplaces can count on high levels of general or basic skills, notably by making firms' investment in human resources more productive. However, as results in the last column show (specification IV), the moderating role of HPWO practices with respect to human capital only holds for On-job training of personnel; by contrast, as main result can be stated that the role of Work changes aimed at the empowerment of employees to make critical decisions in doing their job is universally valid.

As for the controls, we find a counter-productive role of intra-mural R&D activities, which overall supports that investing in internal research does not automatically translate into increases in innovation outcomes; on the contrary, investments in other innovation activities such as R&D contracted out to external agents, the direct purchase of external knowledge and equipment embodied new technology, are confirmed to play a crucial role. These results are

not surprising and in line with previous empirical research signalling that R&D is often not effective in firms active in low-tech industries (statistically dominant in our sample), whilst embodied technological change, besides being highly connected with the organisational changes under study (Piva and Vivarelli, 2004; Rammer et al., 2010), is also more likely to be effective with respect to increasing firms performance across all sectors of the economy (Ortega-Argilés et al, 2009) and particularly in the traditional sectors which mostly characterise the Italian productive system (Santarelli and Sterlacchini, 1990; Conte and Vivarelli, 2005). The relevance of the size of the market across all the specifications supports the positive effect of international competition on firms' innovation performance, likely *via a learning by exporting effect* fostered by the exposure to superior foreign technology as well as through *economies of scale*, which can better enable the firms to cover the large fixed costs of undertaking R&D (Narula, Zanfei 2003). The Lack of demand as a perceived obstacle to innovate, instead, does not seem to significantly influence the firms' innovative choice. As for the non significant coefficients which have also emerged for Firm size and Group membership, these are not surprising given that the key component of the Italian economy is represented by small and medium sized enterprises not belonging to groups. Exception made for KIBS, industry dummies overall confirm Italy's specialization in traditional, low technology and specialized supplier industries (industry low-tech and other services, both highly significant at 1%) and its weaker presence in scale intensive and science based sectors (KIBS turns out to be the most innovative high-tech sector, though with a 5% significant coefficient) . This likely translate into a relatively low profile of both formal and informal interactions with different external knowledge sources (External cooperation and Openness): indeed, these strategies are generally associated with an increased potential for highly novel or radical recombinations of unfamiliar knowledge (Tether, 2002) by firms in high tech sectors; conversely, the Italian productive system is more committed to incremental and embodied technological change, which implies making small scale improvements to add or sustain value to existing products, processes and services.

Turning to multivariate probit estimations in Table 5, a first important result of this exercise can be found in the covariance matrix at the bottom of the table, where highly significant correlations between the residuals are shown. This strongly supports the assumption of interdependence of firms' decisions about how to develop innovations, mainly due to omitted factors jointly affecting them.

Table 5. Multivariate probit regressions (sub-sample of innovative firms)

Explanatory Variables	Dependent variables			
	<i>Generation in-house</i>	<i>Generation in cooperation</i>	<i>Imitation</i>	<i>Adoption</i>
<i>Firm size</i>	-0.0541*** (0.0175)	0.0719*** (0.0162)	0.0217 (0.0179)	0.0379* (0.0195)
<i>Group</i>	-0.1613*** (0.0423)	0.2341*** (0.0389)	-0.0110 (0.0441)	0.1180** (0.0482)
<i>Intra-mural R&D</i>	0.2613*** (0.0266)	0.0300 (0.0231)	-0.0119 (0.0259)	-0.2069*** (0.0298)
<i>Other innovation investments</i>	0.0477*** (0.0164)	0.1619*** (0.0149)	0.1029*** (0.0160)	0.0880*** (0.0177)
<i>Openness</i>	0.0336*** (0.0089)	0.0246*** (0.0081)	0.0285*** (0.0088)	0.0034 (0.0098)
<i>External cooperation</i>	-0.1683*** (0.0573)	0.6119*** (0.0544)	0.2212*** (0.0547)	0.1159* (0.0615)
<i>High_High</i>	0.0637 (0.0595)	0.2101*** (0.0547)	0.1527*** (0.0571)	0.0092 (0.0635)
<i>Low_High</i>	0.1772*** (0.0592)	0.0327 (0.0530)	0.1838*** (0.0571)	-0.0557 (0.0654)
<i>High_Low</i>	-0.0610 (0.0585)	0.0400 (0.0542)	-0.0563 (0.0642)	-0.0086 (0.0686)
<i>Low_Low</i>	omitted	omitted	omitted	omitted
<i>Market size</i>	0.0478*** (0.0181)	0.0557*** (0.0167)	-0.0256 (0.0188)	-0.0459** (0.0202)
<i>Lack of demand</i>	-0.0380** (0.0183)	-0.0242 (0.0171)	0.0285 (0.0195)	0.0336 (0.0214)
<i>Industry high-tech</i>	0.1805 (0.1332)	-0.0937 (0.1179)	-0.1345 (0.1256)	-0.1878 (0.1381)
<i>Industry medium high-tech</i>	0.5275*** (0.0583)	-0.2860*** (0.0658)	-0.2667*** (0.0771)	-0.3709*** (0.0843)
<i>KIBS</i>	0.1164** (0.0818)	0.1201** (0.0533)	0.1019* (0.0577)	-0.0702 (0.0613)
<i>Industry low-tech</i>	0.2126*** (0.0739)	-0.1309** (0.0532)	-0.1145* (0.0612)	-0.2891*** (0.0678)
<i>Industry medium low-tech</i>	0.3019*** (0.0567)	-0.2232*** (0.0671)	-0.1459* (0.0761)	-0.4336*** (0.0896)
<i>Other services</i>	-0.0187 (0.0557)	-0.0152 (0.0543)	0.0633 (0.0606)	-0.2668*** (0.0669)
<i>Construction, retail&distribution</i>	omitted	omitted	omitted	omitted
<i>Constant</i>	0.5346*** (0.0771)	-0.9647 (0.0726)	-1.2875*** (0.0806)	-1.1832*** (0.0884)
	p1	p2	p3	p4
p1	1.0000			
p2	-0.3586***	1.0000		
p3	-0.1637***	0.1312***	1.0000	
p4	-0.3946***	0.0111	0.2352***	1.0000

Likelihood ratio test of H₀: p21 = p31 = p41 = p32 = p42 = p43 = 0

LR chi2(6)= 700.231***

Wald chi2(68)= 1443.62***

Number of obs.= 6371

Log pseudolikelihood= -12255.751

*p<0.10; **p<0.05; ***p<0.01(two-tailed); robust standard errors in brackets.

Results on this estimation overall support that the way firms innovate is linked to the way work is organised to promote exploration, learning and problem-solving activities. Indeed, in accordance with the third hypothesis of this study, the combined effect of HPWO and high human capital (High-High) turns out to be positive and highly significant for Generation in-cooperation compared to Adoption, which confirms that firms where learning and problem solving on the job are supported, and employees are not in a position with a lot of control, tend to be more active in terms of endogenous innovation (i.e. innovation developed, at least to some extent, in-house). The strong complementarities that characterise the interaction among human skills and work organisation within those firms likely compensate for their lack of internal R&D capacities, which are indeed not significant: we can therefore assume that the kind of knowledge on which they found their innovation ability is mostly “practical”, that is generated in work-process related contexts and thus intimately connected with everyday experience and processes of “learning by doing” and “learning by using” (see Hirsch-Kreinsen, 2008; von Tunzelmann and Acha, 2005). Changes in work organisation are instead always effective with respect to Imitation, where they are highly significant (at 1% level) even when coupled with lower levels of highly educated workers; this finding further supports that investing in work organisation could be more important for Italian firms than simply hiring graduated workers and that this category (Imitation) somehow represents an intermediate form of innovative behaviour, which sits comfortably with the decision to distinguish between four levels of technological capabilities of firms according to the way innovation is actually performed. In contrast with Hypothesis 3, however, Generation in-house is instead positively associated with pure organisation oriented strategies (Low_High). In this respect, an interpretative hypothesis can be put forward that distinguishes between, on the one hand, the technological leader countries (such as UK and US) committed to production involving high

internal innovation with intensive use of skilled labour, and on the other the technological intermediate countries like Italy, where formalised processes of knowledge generation internal to the firm play a relatively minor role and are certainly based on a relatively lower share of highly skilled workers. The fact that firms able to develop innovations entirely internally by all means possess a certain R&D intensity (which in this sole case turns out to be significant) should therefore not be viewed as in contradiction with this result: rather, it shows that, compared to other innovation strategies, the internal generation is mainly based on intra-mural technical R&D staff and so on employees that are considered professional innovators (i.e. already expected to be innovative); on the contrary, our hypothesis seem to hold for “regular” employees having a positive impact on innovation due to their knowledge of the operative processes and their creative capabilities, thus even outside the boundaries of their primary job and any formalised R&D activity.

Specific results on the role of other firms’ activities and characteristics allow to better qualifying these findings. As can be seen, investments in other innovation activities different from internal R&D is again homogeneously significant (at 1% level of confidence) across all the different innovation strategies: as previously mentioned, this should not surprise given that the type of technology used by Italian firms is predominantly embodied in physical capital. Informal interaction with external partners (Openness) and External cooperation turn out to be both significant and positively associated with processes of innovation Generation and Imitation compared to Adoption, which overall supports our previous conjectures about the exceedingly relevance of external knowledge sourcing activities for the most innovative firms. Even in these estimations, however, the relation between Firm size and Group membership on the one hand, and firm performance on the other is not straightforward. Indeed, Firm size turn out to be significant and positively associated with Generation in cooperation, which seem to confirm the positive role of firms’ dimension in improving their innovation capacity and thus the Schumpeterian notion that large firms are more likely to succeed in innovation (Schumpeter, 1943); likewise, Group membership supports that being part of a corporate group increases firms’ innovation capacity, since they can more easily benefit from intra-group knowledge spillovers and internal access to finance (Filatotchev *et al.*, 2003). The same variables, however, appear also negatively related to Generation in-house (i.e. the highest level of firms’ capabilities according to our framework) and with a positive association also with innovation Adoption (i.e. the lowest level), thus suggesting conflicting evidence on their effects on the innovation performance of firms. The size of the market (Market size) is also likely to have a positive influence on firms’ capability to innovate, given that such an effect turns out to be statistically significant (at 1%) only with respect to Generation processes. A positive association of this variable could be also expected with Imitation and Adoption, as the innovation diffusion effect, driven by trade, may well exceed the competitive effect raised by international pressure. Instead, the negative coefficients emerged in both cases (though significant only with respect to Adoption) might suggest that, compared to Generation strategies, these modes of performing innovation mainly respond to the needs of the domestic market; this is further confirmed by the negative and significant (at 1%) coefficient found for the Lack of demand as a perceived obstacle to innovate with respect to Generation in-house. Finally, sectorial dummies indicate only a limited influence of the industrial structure in determining the level of firms’ capabilities. Indeed, results show that firms dealing with Generation in-house are rather widespread across high-tech and low-tech industry and service sectors, which contrasts the view (originally put forward by Pavitt, 1984) that innovation strategies tend to be homogeneous between firms belonging to the same production sector, since they are based on the use of similar sources of knowledge, production technologies and learning processes. Firms dealing with Generation in

cooperation and Imitation are, instead, most likely to be active in KIBS (high-tech) whereas adopting firms are mostly concentrated in Construction, retail and distribution (low-tech), which is the chosen reference category.

When we split our sample in order to distinguish between firms in High-tech industry and low-tech sectors (Low-tech industry and Construction, retail&distribution), some interesting differences emerge (see Tables 6 and 7 below)⁸.

Table 6. Probit regressions: setorial analysis

Explanatory Variables	Dependent variable: <i>Technological innovation</i>					
	High-tech industry		Low-tech industry		Construction, retail&distribution	
	I	II	III	IV	V	VI
<i>Firm size</i>	0.0822 (0.0527)	0.0743 (0.0529)	0.0145 (0.0456)	0.0097 (0.0456)	0.0291 (0.0460)	0.0218 (0.0462)
<i>Group</i>	-0.0178 (0.1268)	-0.0092 (0.1267)	-0.1588 (0.1095)	-0.1302 (0.1110)	0.0391 (0.0861)	0.0316 (0.0874)
<i>Intra-mural R&D</i>	-0.0623 (0.0662)	-0.0619 (0.0651)	-0.0622 (0.0656)	-0.0702 (0.0662)	-0.1077* (0.0641)	-0.1158* (0.0641)
<i>Other innovation investments</i>	0.0725 (0.0473)	0.0764 (0.0516)	0.1210** (0.0489)	0.1117** (0.0505)	0.1323*** (0.0431)	0.1173*** (0.0441)
<i>Openness</i>	0.0004 (0.0247)	-0.0026 (0.0246)	0.0261 (0.0247)	0.0226 (0.0248)	0.0178 (0.0212)	0.0119 (0.0211)
<i>External cooperation</i>	0.3295* (0.1750)	0.3286* (0.1755)	-0.0771 (0.1487)	-0.0941 (0.1505)	-0.1158 (0.1586)	-0.1414 (0.1583)
<i>HPWO</i>			0.0884 (0.1566)		0.3147** (0.1265)	
<i>Work changes</i>	0.3439 (0.3193)	0.0790 (0.2004)		0.3651*** (0.1222)		0.3343*** (0.0917)
<i>On-job training</i>		-0.0809 (0.2183)		-0.1422 (0.1259)		0.1998** (0.0972)
<i>Human capital</i>	-0.0291 (0.1382)	-0.2249 (0.1740)	0.1179 (0.1145)	0.0998 (0.1504)	0.1733* (0.0978)	0.1740 (0.1312)
<i>Human capital X HPWO</i>	0.3793* (0.2016)		0.4497* (0.2450)		0.8930*** (0.2798)	
<i>Human capital X On-job training</i>		0.3127 (0.2567)		0.6512*** (0.2458)		0.2371 (0.2078)
<i>Human capital X Work changes</i>		0.2408 (0.2429)		-0.3602* (0.2153)		-0.0712 (0.1866)
<i>Market size</i>	0.1219** (0.0554)	0.1176** (0.0557)	0.0744 (0.0475)	0.0755 (0.0475)	0.1240*** (0.0391)	0.1293*** (0.0392)
<i>Lack of demand</i>	0.0695 (0.0571)	0.0706 (0.0569)	0.0166 (0.0473)	0.0157 (0.0474)	0.0405 (0.0405)	0.0398 (0.0407)
<i>Industry high-tech</i>	omitted	omitted				
<i>Industry medium high-tech</i>	0.0888 (0.2100)	0.0936 (0.2108)				
<i>KIBS</i>	0.2703 (0.2005)	0.2589 (0.2025)				
<i>Industry low-tech</i>			omitted	omitted		
<i>Industry medium low-tech</i>			-0.1152 (0.1206)	-0.1183 (0.1223)		
<i>Other services</i>			0.0127 (0.1279)	0.0033 (0.1309)		
<i>Construction, retail&distribution</i>						
<i>Constant</i>	0.6222** (0.3122)	0.6974** (0.3291)	1.2613*** (0.1946)	1.2308*** (0.1975)	0.6457*** (0.1813)	0.5497*** (0.1850)
	Pseudo R2= 0.0622	Pseudo R2= 0.0652	Pseudo R2= 0.0309	Pseudo R2= 0.0464	Pseudo R2= 0.0476	Pseudo R2= 0.0569
	Wald chi2(13)= 37.38***	Wald chi2(15)= 41.59***	Wald chi2(12)= 27.64**	Wald chi2(15)= 38.06***	Wald chi2(11)= 50.85***	Wald chi2(13)= 64.98***
	Log pseudolikelihood= -292.05752	Log pseudolikelihood= -291.11046	Log pseudolikelihood= -400.79665	Log pseudolikelihood= -394.35655	Log pseudolikelihood= -633.40122	Log pseudolikelihood= -627.21837
	Number of obs= 1868	Number of obs= 1868	Number of obs= 2424	Number of obs= 2424	Number of obs= 2441	Number of obs= 2441

*p<0.10; **p<0.05; ***p<0.01(two-tailed); robust standard errors in brackets.

As probit estimates show (Table 6), contrary to our expectations (Hypothesis 4), we do not find evidence of a clear cut relationship between high-tech and low-tech sectors of the economy, in the sense that positive synergetic effects between HPWO and Human capital are more likely to work for the former, whereas the role of HPWO practices is more likely to be always valid in the latter. Indeed, as can be seen by looking at specifications I, III an IV, the moderating role of HPWO practices with respect to the human capital/innovation link is likely to work equally for firms operating in high-tech and low-tech industry; the same link is also aided substantially by HPWO practices in firms operating in Construction, retail & distribution, though Work changes and On-job training considered singly do not seem to be effective in this respect (column VI). Furthermore, for firms in low-tech industry, we find human resources to be not directly associated with innovation outcomes, unless coupled with On-job training activities, whilst only Work changes are confirmed to play a relevant role *per se*, which means that they are always crucial whatever is the level of the Human capital within the firm.

Table 7. Multivariate probit regressions: sectorial analysis

Explanatory Variables	High-tech industry (I)				Low-tech industry (II)				Construction, retail&distribution (III)			
	Dependent variables				Dependent variables				Dependent variables			
	Generation in-house	Generation in cooperation	Imitation	Adoption	Generation in-house	Generation in cooperation	Imitation	Adoption	Generation in-house	Generation in cooperation	Imitation	Adoption
Firm size	-0.0675** (0.0331)	0.0933*** (0.0285)	0.0602* (0.0308)	0.1280*** (0.0357)	-0.0807* (0.0279)	0.0018 (0.0262)	0.0012 (0.0295)	-0.0153 (0.0341)	-0.0958*** (0.0313)	0.1518*** (0.0315)	-0.0100 (0.0348)	-0.0271 (0.0347)
Group	0.0456 (0.0894)	-0.1896** (0.0781)	0.0660 (0.0864)	-0.0336 (0.0998)	-0.3418*** (0.0713)	0.2840*** (0.0650)	-0.0387 (0.0754)	0.1601 (0.0858)	-0.1056 (0.0660)	0.2073*** (0.0636)	-0.0300 (0.0719)	0.2275*** (0.0726)
Intra-mural R&D	0.2425*** (0.0441)	-0.0180 (0.0379)	-0.0663 (0.0424)	-0.1336*** (0.0484)	0.2609** (0.0446)	0.0792** (0.0380)	0.0293 (0.0422)	-0.2675 (0.0533)	0.2647*** (0.0520)	0.0690 (0.0475)	0.0308 (0.0514)	-0.2110** (0.0596)
Other innovation investments	0.0513* (0.0291)	-0.1401*** (0.0248)	0.0926*** (0.0266)	0.1106*** (0.0292)	0.0009 (0.0271)	0.1815*** (0.0251)	0.1008*** (0.0274)	0.1095 (0.0326)	0.0952*** (0.0301)	0.1713*** (0.0281)	0.1199*** (0.0296)	0.0481 (0.0312)
Openness	0.0428** (0.0176)	0.0191 (0.0148)	0.0318** (0.0155)	-0.0030 (0.0176)	0.0308** (0.0146)	0.0236 (0.0135)	0.0266* (0.0152)	0.0113 (0.0179)	0.0305** (0.0148)	0.0377*** (0.0140)	0.0301** (0.0152)	0.0079 (0.0157)
External cooperation	-0.0331 (0.0976)	0.6007*** (0.0844)	0.2044** (0.0850)	0.1403 (0.0972)	-0.3000*** (0.0929)	0.5495*** (0.0912)	0.2205** (0.0936)	0.2040 (0.1111)	-0.2293** (0.1117)	0.7679*** (0.1213)	0.2733** (0.1124)	-0.1571 (0.1331)
High_High	-0.1236 (0.0917)	0.2736*** (0.0839)	0.1832** (0.0848)	0.1253 (0.0984)	0.1881** (0.1105)	0.1424 (0.1027)	0.0496 (0.1088)	-0.1731 (0.1314)	0.2653** (0.1183)	0.1133 (0.1047)	0.1903* (0.1126)	-0.0880 (0.1216)
Low_High	-0.0382 (0.1702)	0.0039 (0.1357)	0.2932* (0.1508)	-0.0330 (0.1720)	0.3062*** (0.0948)	0.0990 (0.0852)	0.1290 (0.0919)	-0.0465 (0.1124)	0.1482 (0.0839)	-0.0245 (0.0808)	0.2000** (0.0853)	-0.0318 (0.0921)
High_Low	-0.1147 (0.1056)	-0.0861 (0.0911)	-0.0376 (0.1079)	0.0630 (0.1209)	-0.0398 (0.0962)	0.1890** (0.0888)	0.0595 (0.1047)	0.1308 (0.1164)	-0.0372 (0.1044)	0.0414 (0.1037)	-0.2326* (0.1298)	-0.1745 (0.1237)
Low_Low	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Market size	0.1354*** (0.0384)	0.0388 (0.0347)	-0.0823** (0.0375)	-0.1537*** (0.0409)	0.0530* (0.0306)	0.0208 (0.0279)	-0.0095 (0.0318)	0.0071 (0.0360)	-0.0152 (0.0278)	0.1001*** (0.0268)	0.0010 (0.0302)	-0.0101 (0.0310)
Lack of demand	-0.0899** (0.0372)	-0.0180 (0.0325)	0.0336 (0.0361)	0.0340 (0.0409)	0.0188 (0.0300)	-0.0527* (0.0280)	0.0260 (0.0321)	0.0041 (0.0374)	-0.0592* (0.0302)	0.0145 (0.0298)	0.0285 (0.0339)	0.0524 (0.0345)
Industry high-tech	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Industry medium high-tech	0.3632*** (0.1466)	-0.2116* (0.1252)	-0.1317 (0.1311)	-0.1274 (0.1514)	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
KIBS	0.0569 (0.1406)	0.1373 (0.1262)	0.1677 (0.1329)	0.1191 (0.1455)	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Industry low-tech	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Industry medium low-tech	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Other services	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Constant	0.4154* (0.2188)	-0.9001*** (0.1943)	-1.3845*** (0.2135)	-1.4879*** (0.2281)	0.6286*** (0.1350)	-0.8016** (0.1270)	-1.3812*** (0.1444)	-1.4716 (0.1731)	0.7485*** (0.1301)	-1.4238*** (0.1287)	-1.2972*** (0.1449)	-1.0668*** (0.1488)
	p1	p2	p3	p4	p1	p2	p3	p4	p1	p2	p3	p4
	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	p2 -0.4048***	1.0000			p2 -0.3410***	1.0000			p2 -0.3129***	1.0000		
	p3 -0.0821*	0.1517**	1.0000		p3 -0.1481***	0.0881**	1.0000		p3 -0.2074***	0.1430***	1.0000	
	p4 -0.3581***	0.1057**	0.3118***	1.0000	p4 -0.3832***	0.0179	0.2026***	1.0000	p4 -0.3994***	-0.0843**	0.1480**	1.0000
	Likelihood ratio test of Ho: p21 = p31 = p41 = p22 = p42 = p43 = 0				Likelihood ratio test of Ho: p21 = p31 = p41 = p22 = p42 = p43 = 0				Likelihood ratio test of Ho: p21 = p31 = p41 = p22 = p42 = p43 = 0			
	LR chi2(10) = 195.236***				LR chi2(10) = 200.703***				LR chi2(10) = 230.386***			
	Wald chi2(52) = 542.58***				Wald chi2(52) = 482.77***				Wald chi2(54) = 434.31***			
	Number of obs = 1794				Number of obs = 2325				Number of obs = 2252			
	Log pseudolikelihood = -3238.9726				Log pseudolikelihood = -4320.5541				Log pseudolikelihood = -4632.379			

*p<0.10; **p<0.05; ***p<0.01 (two-tailed); robust standard errors in brackets.

Likewise, turning to multivariate probit estimates shown in Table 7, we find the combined effect of Human capital and HPWO practices (High-High) to be effective with respect to augment the innovation capacity of firms in all sectors: indeed, the associated coefficient turns out to be always positively related to strategies of innovation adoption compared to adoption. Moreover, one can notice that positive complementarities between HPWO and Human capital turn out to be more effective for firms in low-techs (especially Construction, retail&distribution), where they lead to innovations developed entirely within the firm (Generation in-house), whereas for high-tech firms they are confirmed to be conducive to innovations developed only in part within the firm (Generation in-cooperation), thus as we have found by testing our model on the complete sample of innovating firms.

5. Concluding remarks and implications for policy

By using firm-level data provided by the fourth round of the (Italian) Community Innovation Survey (CIS 2012), the analysis carried out in this paper contributes to shed light on whether the implementation of advanced work organisation methods within a firm (i.e. new human resources management practices aimed at favouring the upgrading of employees' basic skills through training, at the same time allowing them to use their own ideas and competences by expressing a "creative" effort in doing their work tasks) influences its innovation performance, not only directly, but also *via* reinforcing the link between human capital and innovation. We have also examined the overall effect of human capital and advanced work organisation practices, in order to distinguish between different levels of technological capabilities among innovative firms and thus to identify which combination of these variables leads to the highest level of firms' innovation capacity.

The main findings confirm that not only the acquisition of new skills through the selection and hiring of qualified personnel, but also how personnel management affects individual employees on the work floor should be considered to the development of firms' capabilities. Indeed, work organisation as well as strong positive complementarities or synergy effects between human capital and work organisation have been found to give firms a clear competitive advantage vis à vis both non-innovating firms and firms unable to internally generate new products and processes (i.e. entirely or at least in part by themselves). Moreover, overall results suggest that investing in work organisation could be more important for Italian firms than investing in human resources (i.e. educated labour): indeed, the positive effect of human capital likely depends on the kind of work organisation adopted by a firm (particularly by the provision of on-job training activities), whilst the role of work

changes (particularly the implementation of work changes aimed at increasing employees responsibilities and decision making) is also likely to work individually, that is independently from the level of human skills. These positive effects are present and relevant in both manufacturing and service firms, whilst a bit more differentiated impact has emerged between firms in high-tech and low-tech sectors of the economy: indeed, both the direct and indirect influence of work organisation seems to be particularly strong for the latter. This finding is not surprising given the specific nature of the Italian productive system, characterised by an extreme proliferation of medium, small and micro-sized, enterprises far from the frontier of technological change, where innovation mostly proceeds incrementally, thanks to the “dark” work of many manufacturing engineers, individual inventors and technicians, able to make substantial improvements on products and processes outside any specialised laboratory or formalised R&D activity (Becattini, 2007).

Clearly, these results should be considered in the light of some limitations pertaining the generalizability of the findings, which can be unique to the time period studied, the surveyed firms or the context considered. In particular, they could be influenced by unobserved regional characteristics, an aspect which would need further research. As already mentioned, another main limitation has to do with the cross-sectional nature of the data employed, which does not allow to investigate dynamic relationships and to interpret the results in terms of causality. Nevertheless, some interesting policy implications can be drawn.

So far, the role of work organisation with respect to firms’ capabilities, although widely recognised in theory, has been largely neglected in economic analysis, with little or any attention to issues of workplace organisation as way to enhance opportunities for employees’ workplace learning, skills upgrading and use of creativity. From a policy perspective, this is very much reflected in the fact that work organisation has been rarely taken into account as a policy issue, that is a prerequisite for increasing the innovation performance of firms (see Lundvall and Lorenz, 2014). Conversely, the evidence provided by this study overall supports that it is necessary to move a step ahead of the current conventional wisdom that, in accordance with the linear model of innovation, emphasises the scientific content of technological knowledge applied in (high-tech) firms and, thus, considers that only investments in knowledge through formal education and research efforts are crucial to fostering firms’ innovation and competitiveness. This change of perspective have implications not only for the human resource management of firms (in the precise sense that the quality of employees and their development must be seen as an investment and not merely as an expense), but also for policy makers aiming at supporting innovation: these, in particular, are called for more targeted policy initiatives deemed at encouraging the adoption by firms of the changes needed in workplace organisation, at least by creating the conditions for its effective development and redesign. In this respect, the potential role of workers’ representatives and labour market regulations might be also decisive, as it is shown by the experience of countries characterised by stronger systems of employment protection (mainly Northern European countries): these are indeed characterised by a clear competitive advantage stemming from strategies that places the adoption of new ways of organising work at the centre (see Lorenz and Valeyre, 2005).

APPENDIX A.

Robustness check: Heckprobit results

Since in our second step estimation the analysis has been restricted to a sub-sample of firms able to perform innovation during the reference period (i.e. introducing a product or process innovation), specifically considered as “innovative” for the scope of this study, the inferences presented so far could be influenced by a sample selection bias, which arises when the dependent variable is observed only for a non-randomly restricted sample. Therefore, as robustness check, a probit model with sample selection (Heckprobit) has been also tested on the full sample of 18697 firms.

This model draws on the Heckman’ selection model (Heckman,1979), needed to handle linear regressions when there is a selection bias, except that it has a probit model in the selection equation and a probit model in the outcome equation. Controlling for the selection bias is done by modelling the selection mechanisms explicitly and adjusting the estimation of the parameters in the structural equation for the selection effect, which is obtained by including a correction term (the inverse Mills ratio) in the structural equation. This is calculated from the first stage and reflects how the variables included in this stage are related with the selection of the sample (see Van de Ven and Van Pragg,1981). Hence, applied to this study, this model allows to estimate the probability that a firm will choose one of the four possible options to perform innovation (i.e. Generation in-house, Generation in cooperation, Imitation or Adoption), conditional on the probability of being observed in the sample, namely of being innovative. Thus, the first probit model ($y_1 = x_{11} \ x_{12} \ x_{13}..$) is the selection equation, characterising whether the respondent firm is innovative, whilst the second probit model ($y_2 = x_{21} \ x_{22} \ x_{23}..$) is the outcome equation, describing firm’s dichotomous attitude towards a specific way to perform innovation. Essentially, y_2 is observed only when $y_1=1$, so there are three types of observations in the sample with the following probabilities:

1) $y_1 = 0$ (do not innovate)

$$\Pr(y_1 = 0) = \Phi(-x_1\beta_1) ;$$

2) $y_1 = 1; y_2 = 0$ (innovate but do not choose e.g. Generation in-house)

$$\Pr(y_1 = 1, y_2 = 0) = \Phi(x_1\beta_1) - \Phi_2(x_1\beta_1, x_2\beta_2, \rho) ;$$

3) $y_1 = 1; y_2 = 1$ (innovate and choose e.g. Generation in-house)

$$\Pr(y_1 = 1, y_2 = 1) = \Phi_2(x_1\beta_1, x_2\beta_2, \rho) .$$

Cameron and Trivedi (2005) suggest that, in order to avoid identification problems, it is desirable that at least one regressor in the selection equation is excluded from the outcome equation. Nevertheless, it is difficult to find perfectly exogenous instruments within the CIS, as every question there is closely related. Taking this *caveat* into account, in order to model the selection of the sample, a variable related to *Obstacles to innovation* is considered as exclusion restriction for the second stage, since it is likely to influence the decision to carry out innovation activities, but not to be a determinant of innovation performance. Based on the section of the Italian CIS where firms are asked to rate the relevance of various factors of constraint to innovation activities, from “not experienced” to “highly relevant”, this variable is

created as a binary indicator of whether the firm has perceived at least one of these hampering factors to medium or high degree¹.

The following Table A1 shows the results on the outcome and selection equations for each of the four dependent variables which have been employed in the multivariate probit estimation shown in the main section.

Table A1. Heckprobit regressions (full sample)

Explanatory Variables	I		II		III		IV	
	Generation in house	Technological innovation	Generation in cooperation	Technological innovation	Imitation	Technological innovation	Adoption	Technological innovation
<i>Firm size</i>	-0.0427* (0.0190)	0.0464* (0.0265)	0.0644*** (0.0157)	0.0531** (0.0264)	0.0131 (0.0180)	0.0458* (0.0265)	0.0411** (0.0193)	0.0470* (0.0267)
<i>Group</i>	-0.1491*** (0.0428)	-0.0210 (0.0600)	0.2197*** (0.0373)	-0.0237 (0.0580)	-0.0109 (0.0423)	-0.0124 (0.0586)	0.1143** (0.0473)	-0.0127 (0.0585)
<i>Intra-mural R&D</i>	0.2232*** (0.0393)	-0.0846** (0.0372)	0.0409* (0.0224)	-0.0676* (0.0376)	0.0054 (0.0264)	-0.0773** (0.0377)	-0.2116*** (0.0294)	-0.0800** (0.0371)
<i>Other innovation investments</i>	0.0740*** (0.0187)	0.1374*** (0.0261)	0.1372*** (0.0145)	0.1326*** (0.0253)	0.0756*** (0.0222)	0.1350*** (0.0263)	0.0942*** (0.0176)	0.1407*** (0.0260)
<i>Openness</i>	0.0372*** (0.0087)	0.0230* (0.0135)	0.0205*** (0.0078)	0.0215 (0.0134)	0.0236** (0.0091)	0.0220* (0.0134)	0.0024 (0.0098)	0.0207 (0.0135)
<i>External cooperation</i>	-0.1304** (0.0578)	0.0772 (0.0998)	0.5920*** (0.0537)	0.0639 (0.0909)	0.1988*** (0.0540)	0.0572 (0.0911)	0.0927 (0.0615)	0.0642 (0.0914)
<i>High_High</i>	0.1694*** (0.0560)		0.2122*** (0.0530)		0.1493*** (0.0535)		0.0080 (0.0626)	
<i>Low_High</i>			0.0362 (0.0494)		0.1739*** (0.0549)		-0.0574 (0.0645)	
<i>High_Low</i>	-0.0576 (0.0541)		0.0392 (0.0502)		-0.0546 (0.0591)		-0.0082 (0.0676)	
<i>Low_Low</i>	omitted		omitted		omitted		omitted	
<i>Market size</i>	0.0666*** (0.0186)	0.1178*** (0.0257)	0.0323** (0.0160)	0.1183*** (0.0258)	-0.0475** (0.0200)	0.1146*** (0.0261)	-0.0381* (0.0201)	0.1132*** (0.0261)
<i>Lack of demand</i>	-0.0350** (0.0176)		-0.0190 (0.0159)		0.0266 (0.0183)		0.0415** (0.0211)	
<i>Industry high-tech</i>	0.1831 (0.1304)	0.0501 (0.1919)	-0.1022 (0.1139)	0.0562 (0.1865)	-0.1372 (0.1202)	0.0507 (0.1882)	-0.2051 (0.1366)	0.0594 (0.1890)
<i>Industry medium high-tech</i>	0.5034*** (0.0861)	0.1409 (0.1129)	-0.2890*** (0.0635)	0.1052 (0.1087)	-0.2669*** (0.0741)	0.1256 (0.1070)	-0.3570*** (0.0846)	0.1277 (0.1082)
<i>RIS</i>	0.1595*** (0.0576)	0.3114*** (0.0854)	0.0608 (0.0515)	0.3100*** (0.0848)	0.0392 (0.0658)	0.3051*** (0.0861)	-0.0424 (0.0603)	0.3027*** (0.0858)
<i>Industry low-tech</i>	0.2446** (0.0574)	0.2529*** (0.0884)	-0.1722** (0.0512)	0.2523*** (0.0878)	-0.1534** (0.0606)	0.2665*** (0.0895)	-0.2731** (0.0672)	0.2590*** (0.0891)
<i>Industry medium low-tech</i>	0.2871*** (0.0717)	0.1014 (0.1017)	-0.2335*** (0.0640)	0.1424 (0.0996)	-0.1593** (0.0728)	0.1283 (0.1030)	-0.4035*** (0.0886)	0.1132 (0.1026)
<i>Other services</i>	0.0312 (0.0589)	0.2878*** (0.0893)	-0.0651 (0.0521)	0.2904*** (0.0880)	0.0016 (0.0669)	0.2863*** (0.0872)	-0.2312** (0.0657)	0.2907*** (0.0876)
<i>Construction, retail&distribution</i>	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
<i>Perceived obstacles</i>		0.0957 (0.1092)		0.1174 (0.1087)		0.1504 (0.1121)		0.1094 (0.1137)
<i>Constant</i>	0.2574** (0.1299)	0.6891*** (0.1412)	-0.7157*** (0.0685)	0.6503*** (0.1401)	-0.9878*** (0.1669)	0.6458*** (0.1387)	-1.2780*** (0.0871)	0.6822*** (0.1424)
Rho		0.7500		-0.9148		-0.7089		0.8065
Wald chi2(1) test of indep. eqns. (Rho=0)		21900		1113***		322*		208
Log-likelihood		-4582660		-531342		-4341341		-3782868
Number of obs.		6733		6733		6733		6733

*p<0.10; **p<0.05; ***p<0.01(two-tailed); robust standard errors in brackets.

As revealed by the Wald test for independent equations, only in two regressions out of four the estimated correlations between the error terms are significantly different from 0 (i.e. with respect to Generation in cooperation and Imitation) thus indicating that the two equations should be actually jointly estimated; whereas in the remaining four specifications the estimated correlations between the residuals are not significantly different from 0. Specific results on the variables of interest assessing the role of different combinations of Human capital and HPWO are however robust across all the regressions.

NOTES

1)The 10 sources of information listed in question 6.1 of the Italian CIS are as follows: 1) within your enterprise or enterprise group; 2) suppliers of equipment, materials, components or software; 3) clients or customers from the private sector; 4) clients or customers from the public sector; 5) competitors or others enterprises in your industry; 6) consultants and commercial labs; 7) universities or other higher education institutions; 8) government, public or private research institutes; 9) conferences, trade fairs, exhibitions; 10) scientific journals and trade/technical publications; 11) professional and industry associations.

2) The types of partners for cooperation listed in the Italian CIS are: 1) other enterprises within your enterprise group; 2) suppliers of equipment, materials, components or software; 3) clients or customers from the private sector; 4) clients or customers from the public sector; 5) competitors or other enterprises in your sector; 6) consultants and commercial labs; 7) universities or other higher education institutions; 8) government, public or private research institutes.

3)Although there are several alternative ways of measuring firm's absorptive capacity based on CIS data (see Lewandowska, 2015), this study follows the view (originally put forward by Rosenberg, 1990) that a basic

¹ Eight obstacles or factors of constraint have been used among those listed in the Italian CIS, such as: 1)strong price competition; 2)strong competition on product quality, reputation or brand; 3)innovations by competitors; 4)dominant market share held by competitors; 5)lack of qualified personnel; 6)lack of adequate finance; 7)high cost of access to new markets; 8)high cost of meeting government regulations or legal requirements.

research capability is often indispensable as external knowledge does not automatically fit with the firm's innovation processes.

4)Indeed, the CIS also gathers information on firms that have attempted to innovate without managing to introduce any new product or process, as well as on firms "not innovation-oriented", that is not willing to innovate and therefore not engaged in any innovation activity, which have been thus selected-out of the sample.

5)For a good introduction to the multivariate probit models see Green 2012, pp. 792-795.

6)While Aghion et al. (1999) agree that technological advancements are the main cause of firm reorganisation, Thesmar and Thoenig (2000) claim that the need to reorganise production (and consequently work) within firms should be more generally attributed to a more dynamic and competitive outside environment, which therefore implies "creative destruction" in the Schumpeterian fashion; in line with this, for instance, Osterman (1994), in a study of 694 US firms in 1992, finds that over 60% of firms have introduced new working practices (just-in-time, total quality management, job rotation, team working) which involve significant job reorganisation for over half of the employees, independently of the technological variable.

7)Note that data cleaning and missing observations on some of the variables employed have reduced the effective sample to 6733 and 6371 units, respectively.

8)Note that we have splitted the overall sample of firms into three groups of comparable size in order to keep separated industry (manufacturing and services in high-tech and low-tech sectors) from the residual category encompassing construction, retail and distribution which is, however, statistically predominant (see descriptive statistics).

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