Knowledge-intensive sectors and the role of collective performance-related pay

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KNOWLEDGE-INTENSIVE SECTORS AND THE ROLE OF COLLECTIVE PERFORMANCE-RELATED PAY

ABSTRACT

The main contribution of this study is showing that the efficiency effects of collective performance-related pay (CPRP) are more pronounced in knowledge-intensive service sectors (KISs) than in other sectors. The hypothesis is that human resource practices such as CPRP are particularly useful for enhancing firm performance when innovation-supporting knowledge is distributed among multiple skill sets and employee creativity, knowledge creation and knowledge sharing are key success factors for the firm. Cross-sectional estimates obtained for a national sample of approximately 3,800 Italian firms confirm this prediction. These results are validated by adopting a treatment effect approach to solve the self-selection problem.

Keywords: Collective Bargaining; Performance-related pay; Firm performance

JEL Classifications: D23; J33.

1. Introduction

Studies of performance-oriented human resource management (HRM) systems have gained ground in recent decades (Bryson et al. 2013). Despite mixed findings, there has been a substantial body of strategic HRM research suggesting that high-performance or high-investment HRM systems (which typically include performance-related payments) can enhance knowledge generation, learning and teamwork; these, in turn, affect firm performance (e.g., Collins and Smith 2006; Liu, Gong and Huang 2017; see also Datta, Guthrie, and Wright 2005). Furthermore, research has previously found that collective performance-related pay (CPRP) can foster information and knowledge sharing among employees (e.g., Pearsall et al. 2010). Thus, it is a natural extension of the existing literature to surmise that performance-related payments will work better in a context that requires a high level of knowledge creation and sharing.

However, an issue that is both interesting and under-studied concerns the different effects of incentive pay schemes across industries, especially those that may play a strategic role in a knowledge economy. Indeed, although HRM systems (including compensation incentives) are ubiquitous, there are no prior studies that have focused on the role of wage incentives (individual and/or collective) in predicting the heterogeneous influence of these systems on economic performance across sectors.

In this paper, we argue that there is a need to redirect incentive research to include a consideration of sectoral factors. We expect that in sectors where complex knowledge and multiple sets of skills are important capabilities for firms, the proper design of the compensation structure and the adoption of commitment-based HRM practices may be particularly influential on firm survival and success (Collins and Smith 2006)[i]. Indeed, organizational competencies, intellectual capital and the socialization of tacit knowledge among employees are strategical tools (Nahapiet and Ghoshal 1998), and the reward system can be designed to encourage creation, sharing and utilization of this local knowledge.

This issue has important implications in market services, where the proportion of high-skilled workers has doubled or tripled in recent decades (European Commission, 2012). Particularly in knowledge-intensive sectors (KISs), the largest changes have been frequently characterized as skill-biased (Inklaar, Timmer, and Van Ark 2008). Furthermore, in KISs, innovative activities rely on projects, involve teams of workers that must effectively interact with one another and are, in general terms, less formal than R&D activities performed in manufacturing. Very often, the potential role of KISs in combining different forms of knowledge may help other sectors reach the efficiency frontier with clear evidence of knowledge spill-over effects (Camacho and Rodriguez 2007). Hence, KIS sectors are also important for their function as carriers of knowledge, which influences the productivity of manufacturing sectors (Ciriaci and Palma 2016).

In any case, overall KIS performance in the EU has been found to be largely responsible for the distance between the labour productivity growth of European economies with respect to that of the US (Inklaar, Timmer, and Van Ark 2008, 142). The slow and declining labour productivity growth in services among EU countries, particularly in the Italian case, remains an unanswered question in the ongoing debate. In Italy, over the whole 1995-2016 period, productivity growth recorded a very low figure compared to their main competitors (Bugamelli and Lotti 2018, 20). Thus, our focus on market services may be particularly useful to identify the most efficient HR practices that can contribute to reversing these disappointing results.

Starting from these considerations, this paper aims at analysing the relationship between CPRP and firms' performance (labour and total factor productivity) for the whole Italian economy and different sectors, grouped by the degree of technological and knowledge intensity (Eurostat classification)[ii].

The Eurostat classification allows us to simplify and re-arrange two classes for business services (knowledge-intensive services, KISs, and less knowledge-intensive services, LKISs) and two classes for the manufacturing industry (high and medium-high technology; low and medium-low technology). By doing so, we can verify whether wage incentives reveal a distinctive and additional driver of productivity performance in Italian firms operating in KISs, which in turn have been identified as key industries for the creation of a dynamic knowledge-based economy.

The data we use are obtained by merging statistical information from the Italian National Institute of Statistics (ISTAT) Labour Cost Surveys (reference year 2012), the National Census for Industries and Services conducted in 2011, the National Social Insurance Agency (INPS, reference year 2012) and ISTAT-Chambers of Commerce balance sheets of firms (coverage from 2007 to 2014).

In testing the role of CPRP on firm performance, we take into account the potential self-selection problem, as firms' adoption of collective performance-related pay may be related to firm performance. The occurrence of such self-selection may generate biased estimates, and after OLS regressions, we perform additional estimates adopting the inverse probability weighting with a regression adjustment method (IPWRA) in the version suggested by Wooldridge (2010). Finally, by relaxing the selection-on-observable hypothesis, we attempt to introduce valid instruments and run IV average treatment effect estimates (selection-on-unobservable).

The paper is structured as follows. Section 2 briefly discusses the related literature. Section 3 presents the Italian data that have been used and offers descriptive statistics. Section 4 illustrates the econometric strategy and section 5, the estimation results; section 6 concludes the paper.

2. Literature review

This section concentrates on reviewing literature that supports our research question, that is, studying different impacts of CPRP on the efficiency indicators of firms across sectors, paying specific attention to those industries where innovation processes rely on cooperative behaviour and knowledge sharing, such as KISs. Finally, we debate how firms' performance is measured in studies dealing with CPRP and the economic outcomes.

2.1 Studies on performance-related pay

Studies focusing on the role of incentive pay schemes have documented significant heterogeneities within and across countries (Bryson et al. 2013). However, the different views of leading economists[iii] who have significantly contributed to compensation research by developing theory and conducting empirical studies, clearly show that the link between wage incentives and knowledge management strategy remains an underdeveloped issue (Gibbs 2016). Some economists explicitly admit that little is known regarding organizational structures, innovation processes and social networks within the firm, which may be different across industries (see in particular Gibbs 2016, 18).

To date, to explain incentive heterogeneities, some authors have investigated the adoption of compensation schemes implemented in isolation or as part of bundles of complementary HRM practices (Milgrom and Roberts 1995; Blasi et al. 2016). Other authors have analysed individual versus collective incentive payments (Kruse et al. 2010). There is a widely held opinion that collective wage bonuses linking pay to performance, such as CPRP, constitute a commitment device to align worker and firm objectives and encourage collaborative relationships among employees (see, among the other reviews, Weitzman and Kruse,1990; OECD 1995; Bryson et al. 2013). In particular, it has been posited that collective wage incentives are assumed to have beneficial effects on productivity through three distinct channels: '(1) increasing worker effort; (2) increasing the skills of the workforce; and/or (3) increasing the flow of information within the organization' (Kruse, 1992, 24). However, collective bonuses are not exempt from potential drawbacks (Ben-Ner and Jones 1995). The very fact that they are collective may encourage employees to shirk and free-ride on the efforts of others, causing underperforming results in terms of firm productivity[iv].

Furthermore, individual payment-by-result might play a primary role in selection, hiring and retention because the enterprise can use these schemes to attract high-ability workers and those that are particularly optimistic about the firm's prospects; hence, these schemes reduce attrition among the most productive employees (Lazear 1999). However, as discussed by Bryson and Freeman (2010, 205), while group payments encourage employees to work cooperatively, individual payment for performance can induce some employees to sabotage the output of others, especially if that might increase their probability of a promotion. Bryson and Freeman (2010) suggest that both types of incentives (collective and individual) may be useful and that their complementary usage is needed for maximizing output. On the one hand, teamwork and group-based incentive payments are relevant when the skills of a single employee enhance those of co-workers within the team (Lazear and Shaw 2007). It can be added that creating a social climate of cooperation is strategical for knowledge-intensive firms, where employees might see their competences and tacit knowledge as sources of job security and power and thereby be reluctant to share their knowledge with co-workers (Davenport and Prusak 1998). On the other hand, individual pay for performance may provide a tool to combat the temptation to free-ride on the group and thus can complement collective incentive payments. These collective and individual HRM practices can be combined and could then increase firm performance more than either would if adopted independently (Lazaear and Shaw 2007). As empirically found by Pearsall et al. (2010), hybrid rewards (that combine team and individual schemes) lead to higher levels of performance, and these effects are due both to improvements in information allocation and reductions in social loafing, defined as the reduction in effort and motivation that tends to occur when individuals work collectively.

However, the actual diffusion in the Italian economy of individual bonuses linked to performance is rather limited. Studies based on statistical sources alternative to those used in this empirical analysis clearly show only a small incidence of these individual premiums (Damiani and Ricci 2014). This evidence may be partly explained by the high union density rates recorded in the Italian economy, which has recorded a slower and more contained downward trend than elsewhere and is still one of the highest rates in the world (Leonardi and Pedersini 2018). Indeed, the influence of worker organizations usually supports inclusiveness and solidarity clauses in collective agreements and the achievement of improvements in economic conditions on a broad front, rather than the development of incentives to reward individual skills and high-level jobs. Additionally, the database we use offers information that indirectly confirms the limited incidence of individual incentives, as can be seen below (section 3.2).

For the reasons above, in our analysis, we try to ascertain only the peculiar role of collective incentive pay (CPRP) in firms operating across different sectors.

Especially in those sectors such as KISs, where knowledge, rather than physical or financial capital, is the most important input of firms, one can expect that collective incentives activate information *sharing* among co-workers and may also be directed to support the knowledge *creation* process.

2.2 Performance-related pay in knowledge-intensive sectors

Recent reviews of the strategic HRM literature (see Liu, Gong and Huang 2017) indicate that a fruitful area for research is to adopt a contingency approach to explore when HRM practices function more or less effectively (Jackson et al. 2014; Liu, Gong and Huang 2017). The contingency approach has seen limited use to verify how performance practices are affected by structural variables such as technology and market context, which typify the different sectors (Datta, Guthrie, and Wright 2005; Conray et al. 2015).

Some industry characteristics could explain why workers' capabilities may have a greater impact in KIS than in manufacturing sectors.

First, management and economic studies show that the *relative* importance of HRM practices, such as commitment-based pay, is influenced by industry capital intensity (Datta, Guthrie, and Wright 2005). Indeed, although capital-intensive sectors may record high employee skill levels and higher wages, capital intensity often creates strategic rigidity because fixed costs are high, emphasis is on asset management and cost control, and deviations from past practices are very expensive (Datta and Rajagopalan 1998). Capital-intensive firms are more focused on the degree of automation of the production technology and the related task structure, which greatly constrain employee performance (Terpstra and Rozell 1993, 43). By contrast, 'the human element becomes more integral to the production process as capital intensity decreases' (Datta, Guthrie, and Wright 2005 137). This is the distinctive aspect of KISs, where the human factor and intellectual capital play a central role. The same criterion of classification adopted by Eurostat reflects this point because a service activity is classified as knowledge intensive if persons achieving a tertiary education represent more than 33% of the total employment in that activity (European Commission 2012). Thus, the relevance of 'filling knowledge gaps' instead of 'job filling' (Brelade and Harman 2000) is a typical trait of KISs. Starbuck (1992) notes that knowledge should be understood not as a flow of information but as a stock of expertise, so that a firm should be considered knowledge-intensive when 'exceptional and valuable expertise dominates commonplace knowledge' (Starbuck 1992, 716).

Second, commitment-based rewards are less beneficial for manufacturing line employees than for knowledge workers, as argued by Collins and Smith (2006). Some positive effects may be related to the value-creating potential of high skills, as well as the uniqueness of these skills to a particular firm (Lepak and Snell 1999, 35; Collins and Smith 2006). Thus, we expect that CPRP may be more beneficial for sectors where knowledge workers represent the vast majority of the workforce, such as KISs. This is particularly true in the Italian institutional setting, where most firms pay collective incentives at the firm or establishment level and lack the ability to differentiate incentives for line and knowledge workers.

Third, innovation and capabilities in services are different from innovation in manufacturing (Hipp and Grupp 2005). In KISs, the peculiar core competences of employees reside in their ability to combine *codified* scientific and technical knowledge with *tacit* knowledge based on previous experience (Gotsch and Hipp 2012). Especially in some KIS subsectors (computer and software consulting, legal and technical services, advertising, research and development)[v], innovation is not generated by single special departments but emerges during daily experiences and in cooperation with clients; furthermore, it is not protected by patents nor is it acquired through formal R&D investment. Thus, in KISs, compared to the technologically oriented processes of manufacturing, service innovations are intangible in nature, and the knowledge supporting them is distributed among multiple skill sets and is not easily programmable. In addition, knowledge sharing and cumulative learning arising from relationships among users and suppliers have a central concern (European Commission 2012).

In summary, a lower industry capital intensity, a higher percentage of knowledge workers, and the peculiar traits of innovation and capabilities are all moderating factors likely influencing a specific relationship between collective wage incentives and economic performance in KISs.

Concerning collective versus individual wage incentives, note that knowledge and expertise are sources of power that may be limited by disclosure; thus, the lack of motivation to transfer knowledge to colleagues is a serious concern, and well-designed management systems must remedy this reluctance to share expertise, particularly in cases of tacit knowledge, whose propagation calls for socialization and apprenticeship (Srivastava et al. 2006). Reward schemes, which are contingent on firm outcomes that require knowledge sharing to be obtained, increase workers' willingness to share knowledge and mitigate uncooperative attitudes.

However, the OECD report also highlights that specific activities in KISs require not only team work but also the efforts of individual workers to update their knowledge and individual learning to develop solutions for specific clients (OECD 2006).

In addition, innovation is a function of both individual and group creativity, and knowledge is a key component of creativity (Amabile 1996). Thus far, only a few empirical studies have examined how knowledge affects the individual generation of new and useful ideas in the workplace, as observed in the extensive survey of Anderson, Potočnik, and Zhou (2014). Furthermore, the role of rewards in facilitating or hindering creativity remains an unsolved puzzle because the impact of individual rewards on creative behaviour may be mixed (Anderson, Potočnik, and Zhou 2014). For instance, Deci and Ryan (1985) argue that contingent base rewards may be viewed as an attempt to control individual behaviour that lessens innovative attitudes. Conversely, Einseberger et al. (2009) find that contingent rewards reveal the desire of givers to obtain collaboration from their subordinates and thus make cooperation easier between the potential recipient and the reward givers.

All these considerations signal that the joint analysis of individual and collective bonuses would be the preferred option (Anderson, Potočnik, and Zhou 2014). Unfortunately, as stated above and explained in more depth in section 3.1, the SICA-LCS survey we use does not provide data on enterprises that adopt individual incentives. Future research, also based on other country studies, might investigate the potential complementarities of different incentives at the individual and team levels.

2.3 Incentive pay and firm performance

In our analysis, we examine the role of wage incentives on efficiency. Literature on outcomes of the incentive pay system often examines indicators of profitability and efficiency (Park and Kruse 2014; Bryson et al. 2013). Indeed, the latter may also be conditioned by a number of organizational factors (Park and Kruse 2014) that we cannot control for in our econometric analysis. Furthermore, it is worth noting that in the Italian case, productivity is the main factor holding back long-term economic growth; hence, measures to promote performance-based rewards are a relevant issue in the long-debated slowing of the growth rates of the Italian economy (Bugamelli and Lotti 2018).

According to Syverson (2011), the efficiency indicators primarily used among scholars are labour productivity (LP) and total factor productivity (TFP). As is well known, the former is a measure of single factor productivity affected by the intensity of use of excluded inputs (capital *in primis*). Even when a control for capital intensity is introduced, the endogeneity between capital and value added remains a major concern. TFP solves these problems and better reflects technological change, the quality of inputs, and the management and organizational capabilities of firms. Regardless, using TFP as a measure of technical efficiency is not completely trouble-free. Some authors criticize TFP's high sensitivity to the assumptions concerning the underlying production function (Bottazzi et al. 2010). Others argue that TFP measures not only technological change, but also market power if we are not able to control for output price heterogeneity across firms (De Loecker and Goldberg 2014; Bugamelli and Lotti 2018).

Given this even distribution of *pros* and *cons* between LP and TFP, in this study, we maintain both measures of productivity. Overall, we expect that CPRP positively affects LP. This evidence would also provide us feedback on the reliability of the magnitude of the CPRP impact, as we can compare this result with those from other studies on Italy (Bryson et al. 2013; Lucifora and Origo 2015), which mainly used LP as the only outcome variable. In addition, we expect a positive influence of CPRP on TFP, which, among other things, is also a proxy for organizational capabilities and quality of labour. Whether collective incentive pay particularly boosted TFP in KISs could indicate whether collective bonuses spur motivation and knowledge sharing in contexts where team- and project-based working matter.

3. Data and descriptive statistics

3.1 Data

As mentioned in the introduction and further explained in the section dedicated to the econometric strategy, we attempted to solve the self-selection problem in our cross-section sample by enlarging as much as possible the set of control variables concerning the firm's characteristics to make plausible the assumption of *selection on observables*. This led us to combine four different data sources that ISTAT made available for our analysis: i) Labour Cost Survey (LCS); ii) National Social Insurance Agency (INPS); iii) National Census for Industries and Services (NCIS) and iv) firms' balance sheet.

As regards the explanatory variables, our empirical analysis is mainly based on information obtained by LCS that was conducted by ISTAT in 2012 on a representative sample of firms with more than ten employees operating in the private non-agricultural sector. The information used in this paper is gathered from the separate section SICA (Sistema Informativo sulla Contrattazione Aziendale) of the ISTAT LCS, see Cardinaleschi (2013). The SICA-LCS survey collects data about the various components of labour costs determined at different levels of the wage bargaining.

Note that the Italian institutional wage setting is characterized by a two-tier bargaining regime. In this regime, first-level wage contracts at the sectoral level are intended to guarantee the purchasing power of wages and thus set wage increases linked to the target inflation rate; the second level of bargaining, at the firm level, distributes wage premiums, which may be of a fixed amount or linked to productivity or profit results. Concerning the performance-related pay schemes, SICA-LCS data mainly refer to variable bonuses paid to all employees. These schemes are distinct from more traditional fixed bonuses, which are offered independently from firm results. Regarding the variable collective bonuses, the SICA-LCS survey distinguishes among schemes determined in reference to a variety of economic indicators of company performance, such as the achievement of profit, productivity of teams, and quality targets. This information should permit us to verify the peculiarities of risk sharing participatory schemes (linked to profit targets) and incentive schemes (linked to productivity and quality indicators). Thus, we obtain five typologies of targets: i) profitability, such as gross operating margins, and other budgetary measures; ii) team productivity, which includes basically any kind of measures of technical efficiency and labour productivity obtained at the team and establishment levels; iii) quality, a group of indicators that includes the number of defective outputs, the percentage of discarded products and customer complaints; iv) attendance, which refers to the presence of workers and permits to monitor and evaluate absenteeism; and v) *other*, that is a residual group. Of course, collective bonuses are distributed when some of these targets are achieved. Furthermore, for firms that achieve these targets, the SICA-LCS survey asks about the criteria adopted to distribute bonuses to their workforce. Again, five different categories of criteria are available: i) attendance, ii) job titles[vi], iii) individual acquisition of competencies and skills, iv) acquisition of relational competencies, implementation of team production processes and efforts to support customer relations; and v) compliance with functional flexibility (working time changes, multi-tasking or task changes)[vii]. However, notice that, in our econometric analysis, we cannot consider all this detailed information because the limited number of observations for each variety of schemes does not permit us to obtain reliable distinct estimates for every type of incentive. Therefore, we use this detailed information only in descriptive statistics, which, regardless, help us to corroborate the econometric results.

In any case, the SICA-LCS section provides information about the adoption of firm-level bargaining, and each firm is asked whether a CPRP scheme has been adopted[viii]. Therefore, our key explanatory variable is a dummy variable indicating the existence or not of a CPRP scheme of some kind. To establish a sufficient time lag and to alleviate endogeneity problems among this key regressor and the outcome variables, we only considered firms for which CPRP was introduced before 2012 and excluded those implementing this scheme as new scheme in 2012. Additional information on the payment of the so-called 'guaranteed element of remuneration' (Elemento di Garanzia Retributivo), which is a fixed bonus established at the first-level of bargaining, is also gathered by SICA-LCS and has been included in the analysis as control. From the same survey, we draw information on workforce characteristics and labour relations (fixed-term and part-time contracts, trained employees, composition by gender, presence of unions) and firm characteristics (size classes in terms of employees, industry and geographical location).

According to the literature (Belot et al. 2007), job tenure could influence the firm performance, hence we resort to INPS to obtain this information, which refers to 2012. Other useful aspects of firm business strategy (product and process innovation, export orientation and multinational status) are obtained by statistical data collected by the National Italian Census for Industries and Services for the end of 2011.

Eventually, the balance sheet information (from 2007 to 2014 in our case) that ISTAT draws from the Chamber of Commerce archives allow us to define two efficiency indicators. These two variables have been obtained as averages over the years 2013 and 2014 to insert a reasonable time interval between CPRP (already implemented before 2012) and the firm performances. These two indicators are a standard labour productivity measure (the ratio of value added to employment), and the TFP, that we estimated with the method explained in section 4. Only for this derived variable (TFP), inputs and outputs of the firm-level production function over the whole available 2007-2014 period have been taken into account, then we average residuals over 2013-2014.

From the Chamber of Commerce archives, we also gather information to construct a profitability indicator, that is the return on sales (ROS)[ix]. In more details, we take the average of ROS over the 2007-2010 period and use this indicator of past profitability (ROS_2007-2010) as an instrument, among others, to test strong endogeneity and *selection on unobservables* for our key explanatory variable, that is CPRP (see section 4). On the one hand, the past profitability is considered in literature as a proxy of the 'ability to pay' of firms, the latter being strongly associated with the implementation of HRM practices and incentive pay systems (Park and Kruse 2014). On the other hand, past profitability is not always a driver of efficiency, especially across Italian firms, as pointed out by Bottazzi et al. (2010). Based on these considerations, we assume that ROS_2007-2010 may be an instrument for CPRP because it influences the probability that firms introduce CPRP schemes but at the same time does not necessarily influence the efficiency indicators.

The statistical classification of economic activities is obtained by applying the NACE rev.2 classification at two digits, and sectors are grouped, following Eurostat, into distinct classes: two classes for the manufacturing industry (high- and medium high-technology, low and medium low-technology)[x]; two classes for services (knowledge-intensive services, KISs, and less knowledge-intensive services, LKISs) and a residual group that includes Mining and Quarrying, Electricity and Gas, Water Supply and Construction.

By combining all four datasets, we obtain a sample of 3,806 firms. This sample is restricted, compared to the maximum number of observations available for only the SICA-LCS dataset (more than 6,000 firms). This important reduction in the sample size is the price we accepted to pay to increase the number and quality of observable firms' characteristics, which makes more plausible the implementation of a treatment effect method based on *selection on observables*.

3.2 Descriptive statistics

Descriptive statistics of our sample are reported in Table 1. The first column shows the main characteristics for the whole economy, whereas the other columns report the results for the distinct groups of industries. Note that in our sample, the highest share of firms is recorded in L&M_Tech sectors (28%) and LKISs (26%), summing to more than fifty% of the whole sample (54%). A total of 23% of firms are in KISs, while the lowest share is found in H&M_Tech, with only approximately 13%.

As expected, the most advanced sectors, H&M_Tech and KISs, although less represented, show the highest values for labour productivity and very high values for TFP[xi]. In particular, for both indicators, the highest values are recorded for H&M_Tech (above the average of the whole economy), followed by those for KISs. We also note the low percentages of exporting firms in KISs and LKISs (28.23% and 27.18%, respectively), which are below the higher values recorded in the other sectors (85.28% in H&M_Tech and 78.46% in L&M_Tech)[xii].

As expected, both service industries have a lower degree of capital intensity than does manufacturing, as shown by the amount of capital per unit of work (measured by the ratio of capital to employees). However, a significant differential between the two groups is noteworthy. Indeed, KISs, notwithstanding a low value of capital to labour, record higher values for both efficiency indicators, likely reaching this superior efficiency performance through the accumulation of human and intellectual capital.

In terms of the enterprise dimension, we observe that KISs are predominantly characterized by small firms, more than manufacturing and more than LKISs. In particular, KISs show the highest incidence of firms with fewer than 50 employees, as the share of firms in the class with 10-49 employees is 55.64% of the whole sector, in comparison to only one-third of the LKISs. The small size of firms operating in KISs is also associated with the lowest values of unionization (32.78%), well below the figures found in the other sectors. Also remarkable, KISs hold the highest percentage of fixed-term contracts (20.66%), the lowest mean values for job tenure (7.56 years), and the highest share of women (approximately half of their workforce). Furthermore, firms operating in KISs are not particularly active in terms of outlays for technological innovation projects, as firms involved in product and process innovation record percentages of 41.37% and 31.23%, well below the values found in both manufacturing industries. In contrast, the highest incidence of innovation is registered in H&M_Tech, where 74.19% and 58.32% of firms are involved in product and process innovation, respectively. However, it is remarkable that firms operating in KISs offer more opportunities to their employees in terms of training, as one-third of them conduct training programmes for more than 50% of their employees. The percentage of firms performing training programmes with high coverage is much lower in the L&M_Tech (19.33%) and H&M_Tech sectors (16.06%).

Interestingly, for our analysis, the key variable CPRP, which captures the adoption of collective wage incentives, shows a limited diffusion in KISs and LKISs, where these schemes are adopted only by 6.93% and 6.16% of firms, respectively. In contrast, in manufacturing, the incidence of CPRP is higher (13.77% and 11.44%, in H&M_Tech and L&M_Tech, respectively).

Additional information to obtain a thorough picture of collective bonuses is reported in Figure 1, where we observe the distributions of firms adopting CPRP according to different targets. First, this figure shows that profit targets are the most common indicators across sectors, as they are used by more than 50% of firms paying collective bonuses. Concerning the quality target, a clear divergence emerges between the manufacturing and service sectors. For manufacturing (H&M_Tech and L&M_Tech industries), the quality indicator is more important; indeed, it is the most important indicator in L&M_Tech sectors. This finding is easily explained because in manufacturing, a key objective is to reduce defects and waste. Conversely, in the tertiary sector, the low incidence of quality targets can be explained by a number of obstacles stemming from intangibility, the absence service quality standards and the intrinsic difficulties in ascertaining their suitability prior to engaging with them (OECD 2006). Particularly in KISs, the importance assigned to project-based work explains why the second most important target is the productivity improvement of teams, considering that 40% of firms adopting CPRP choose this objective. Among the criteria adopted to distribute wage premiums (see Figure 2), we find in KISs, a sector characterized by high-skilled employees and labour-intensive processes, that job titles have a more meaningful role, while attendance has a minor incidence (see Figure 2). In addition, it is remarkable that in KISs, the acquisition of relational competencies and improvement of team capabilities are much more important than they are in high- and medium-high-tech sectors (14% vs 7% of firms, respectively). This finding confirms the necessity in KISs of favouring knowledge sharing and interactive processes among organizations with multiple skill sets. In LKISs, functional flexibility (e.g., the rotation of jobs and tasks, shifts and flexibility in working time) is particularly relevant. The opposite result is evident for KISs, a sector where employee abilities are more complex, more difficult to acquire and involve more job autonomy, thus making a high degree of firm internal functional flexibility less efficient. In sum, this preliminary evidence signals the potential importance of sectoral characterization of incentive pay systems. We will test this hypothesis below.

TABLE 1, HERE

FIGURES 1 AND 2, HERE

4. Econometric method

As we mentioned above, we calculated dependent variables (i.e., labour productivity and TFP) as an average for the years 2013 and 2014. This ensures that the information on CPRP (reference year 2012) is sufficiently lagged with respect to firm economic and financial performance. TFP is an estimated variable obtained with a two-step estimation procedure similar to that applied by Black and Lynch (2001). Specifically, in this case, we used longitudinal data concerning the balance sheets of the firms of interest for the period 2007-2014 and estimated a Cobb-Douglas production function by implementing the GMM_SYS estimator (see Table A.1 in the Appendix). Then, we calculated the average residuals for each firm only for the years 2013 and 2014. The variable TFP could be a more refined index of productivity, especially if value added, capital and labour are simultaneously chosen or if there are measurement errors for the proxy of the capital stock (Black and Lynch 2001).

After this preliminary estimation, we perform an OLS regression on our cross-section sample, as indicated in equation 1:

(1) $lnTFP_{\ i} = \alpha + \beta \cdot CPRP_i + \ \vartheta \cdot \boldsymbol{F}_i + \mu_s + \gamma_j + \varepsilon_i$

where lnTFP_i is the log of the TFP at the firm level (i=1, …3,806), and CPRP represents our key dummy variable indicating the presence of a collective performance-related pay scheme. The vector $\boldsymbol{F}_i$ denotes controls for workforce characteristics (shares of temporary and part-time contracts, shares of women, share of firms that trained more than 50% of their employees, average job tenure) and for firm characteristics (size of classes, process and product innovations, export propensity, multinational enterprises). Moreover, $\boldsymbol{F}_i$ also includes dummies for institutional factors that vary across firms and could affect performance, such as the presence of unions and fixed bonuses established at the sectoral level of the wage bargaining (the so-called 'Elemento di Garanzia Retributivo', EGR). The parameter μ_s denotes sector dummies, γ_j denotes regional (NUTS1_level) dummies, and ε_i is the error term capturing the idiosyncratic component of TFP.

As we discussed in section 2.4, TFP could be sensitive to the assumptions underlying the production function specification. In addition, we need terms of comparison with other studies focused on Italy to know if the CPRP impact on efficiency lies in reliable ranges. Because these studies are based on labour productivity, we also maintain the labour productivity equation as corroborating analysis:

(2) $LP_i = \alpha + \beta \cdot CPRP_i + \lambda \cdot ln\left(\frac{K}{L}\right)_i + \ \vartheta \cdot \boldsymbol{F}_i + \mu_s + \gamma_j + \varepsilon_i$

where LP_i now represents labour productivity, and the number of observations is again i= 1, …3,806. It is worth noting that in this case, it is rational to control for $ln\left(\frac{K}{L}\right)_i$, which is the (log of) physical capital per employee, to consider heterogeneity in capital intensity across firms. All other terms of equation 2 are exactly those we previously discussed for equation 1.

Since investigating different effects of CPRP across sectors is one of the main interests of the study, we replicate all estimates above for the industries grouped according Technological or Knowledge intensity. This means that we re-run equations 1 and 2 for High- and Medium-High-Tech (H&M_tech), Low- and Medium-Low-Tech (L&M_tech) sectors of manufacturing; Knowledge-Intensive (KISs) and Less-Knowledge-Intensive (LKISs) service sectors and a residual group named Other (Mining and Quarrying, Electricity and Gas, Water Supply and Construction).

There is currently large consensus in the econometric literature that a simple OLS regression does not always work well (Angrist and Pischke 2009; Wooldridge 2010; Imbens 2014). If we observe the CPRP adoption from the point of view of the treatment effect literature, it is plausible to wonder if firms implementing this incentive pay scheme would have performed well anyway. For example, if the covariate distributions differ substantially by treatment status and CPRP firms are also the larger ones or more frequently are multinational firms, it means that the treatment variable (CPRP) is not independent from our outcome variables, which are different indicators of firm performance. Therefore, our key OLS coefficient β could be upward biased. This self-selection problem is particularly severe in cross-sectional samples because we are not able to control for firm unobserved heterogeneity by implementing fixed effects estimation.

For this reason, we established a counterfactual setting and attempted to solve the self-selection problem by adopting a treatment effect approach that relies on *i) ignorability (or unconfoundedness)* and *ii) overlap* assumptions (Wooldridge 2010; Imbens 2014).

If we set y_0 a generic outcome variable (TFP or LP), we can express the ignorability assumption as the following:

(3) $$E(y_0| \boldsymbol{F}, CPRP) = E(y_0| \boldsymbol{F}) \text{ and } E(y_1| \boldsymbol{F}, CPRP) = E(y_1| \boldsymbol{F})$$

where y_0 is the performance that the firm would have if it did not adopt CPRP and y_1 is the performance that it shows if it did; thus, CPRP is now our treatment and **F** the set of covariates reported above. The idea underlying this assumption is that if we can observe enough information contained in **F** that determines treatment, then y_0 and y_1 might be mean independent of CPRP, conditional on **F**. In other words, even though (y_0, y_1) and CPRP might be correlated, they are uncorrelated once we partial out **F**.

The overlap assumption:

(4) $$0<P(CPRP=1 \mid \mathbf{F})<1$$

means that for any setting of covariates in the assumed population, there is a chance of seeing units in both the control and treatment groups.

Based on these crucial assumptions, we used an IPWRA approach that combines two different methods to correct the self-selection bias and identify the average treatment effects of treated (CPRP_ATET).

The regression adjustment (RA) uses a two-step approach to estimate the average treatment effects:

1. In the first step, RA fits separate regression models of the outcome on a set of covariates for each treatment level (firms adopting or not adopting CPRP). These regressions predict potential outcomes adjusted for covariates. For example, for each CPRP firm (treated units), the Potential Outcome (POM) calculates the counterfactual performance, i.e., the TFP or LP, the firm would achieve if it did not adopt CPRP. This is possible because for every treated unit, we hopefully have some units in the control group with similar values for the covariates. Similarly, a POM is calculated for non-CPRP firms.

2. In the second step, RA computes the averages of the predicted outcomes for each subject and treatment level. These averages reflect the potential outcome means (POMs). The differences of these averages provide estimates of the average treatment effects (ATEs). In our case, we calculated the only average treatment effect on the treated (ATETs). Thus, the POM is the average of the counterfactual performance predicted for firms adopting CPRP, i.e., the TFP or LP it would achieve if it did not adopt CPRP.

Inverse Probability Weighting estimators (IPW) use weighted averages of the observed outcome variable to estimate means of the potential outcomes. The weights account for the missing data inherent in the potential-outcome framework. Each weight is the inverse of the estimated probability that an individual receives a treatment level. Outcomes of individuals who receive a likely treatment get a weight close to one. Outcomes of individuals who receive an unlikely treatment get a weight larger than one, potentially much larger.

IPW estimators model the probability of treatment without any assumptions about the functional form for the outcome model. In contrast, RA estimators model the outcome without any assumptions about the functional form for the probability of the treatment model.

According to Wooldridge (2010), we can combine RA and IPW to achieve some robustness to misspecification of the parametric models. The resulting estimator is said to be doubly robust, as it only requires either the conditional mean model or the propensity score model to be correctly specified but not both.

IPWRA estimators use the inverse of the estimated treatment-probability weights to estimate missing-data-corrected regression coefficients that are subsequently used to compute the POMs. In other terms, IPWRA has a specific two-step procedure: in the first step, the probability of treatment (CPRP, in our case) is estimated by means of the propensity score, and in the second step, mean conditional models (RA) are adopted using the weights given by the inverse of the probability of treatment.

A number of studies adopt the IPWRA method. Meara et al. (2017) used this approach to study the gender wage gap in the US when other control variables cannot be considered exogenous, such as part-time labour status and education. By means of IPWRA, it is possible to control for gender, part-time contract and education, which are simultaneously correlated with the women wage levels. As stated above, we have similar problems in observing the impact of CPRP on firm performance and controlling, among other factors, by firm size and multinational enterprises (MNE). Indeed, in our case, there is a high probability that the firm size and the MNE character influence the treatment (CPRP) and simultaneously determine the firm performances. A thorough discussion of the IPWRA method is offered by Wooldridge (2010) and another interesting application is provided by Frölich et al. (2017), who test the efficacy of active labour market programmes in Switzerland. Cerulli (2015) discusses the application of IPWRA in the evaluation of socio-economic programmes and R&D policies.

However, the IPWRA estimator is consistent if the *ignorability assumption* holds, and self-selection is based on *observables*. In contrast, whether self-selection is based on certain unobservable factors, we need an instrumental variable method to solve the problem. For example, if the implementation of CPRP also depends on manager capabilities, and this information is not adequately captured by the control variables we use (firm size, multinational enterprise, export or innovation capabilities), the treatment is correlated with the error term such that differently from expression 3, we have

(4) $E\left(\varepsilon_{i,0} \middle| CPRP_i\right) \neq 0$ and $E\left(\varepsilon_{i,1} \middle| CPRP_i\right) \neq 0$

where i is the firm-level observation, and 0,1 are treatment and non-treatment status, respectively.

Although finding valid instruments in our case is not a simple task, we attempted to detect *selection on unobservables* in our data as a further robustness check. Thus, we re-estimated ATET using an instrumental variable approach and then tested the presence of strong endogeneity reported in the expression (4). Again, according to Wooldridge (2010), we used a control-function estimator based on the following statements:

(5) $E\left(\varepsilon_{i,j} \middle| CPRP_i\right) = E\left(\varepsilon_{i,j} \middle| E(CPRP_i|\boldsymbol{z}_i) + v_i\right) = E\left(\varepsilon_{i,j} \mid v_i\right) = \xi v_i$

where i are firm-level observations; j =0,1 the treatment status; $\boldsymbol{z}$ is a matrix containing both included (control variables previously used in equations 1 and 2) and excluded instrument (past profitability) that we discussed in section 3.1[xiii]; v is the unobserved component. Expression 5 tells us that we can isolate the unobserved component by fitting a first step probit regression of CPRP on $\boldsymbol{z}$ to obtain $\hat{v}$ as difference between CPRP and $E(CPRP_i|\boldsymbol{z}_i)$. In the second step, we add the residuals $\hat{v}$ to the equations 1 and 2 estimated with the regression adjusted method. This means that, for each equation, we can estimate and test the correlations between *unobservables* and the error term reported in expression 4, for both outcome model 0 (CPRP=0) and outcome model 1 (CPRP=1). In testing the joint significance of these two correlations, we perform an endogeneity test that informs us about the necessity of using the IV treatment effect method. If we cannot reject the null hypothesis of no correlation between CPRP and error term, IPWRA is the appropriate estimator to use (Wooldridge 2010).

5. Estimation results

Before discussing the regression results, we present a correlation matrix of all variables used in the empirical analysis. The high number of covariates, we use to meet the *ignorability assumption* discussed above and to make a self-selection problem only based on *observables* plausible, raises a concern of redundant explanatory variables and potential multicollinearity in the estimates. Indeed, Table 2 shows very low pairwise correlations among the majority of cells referring to covariates. In only a few and expected cases do we find associations that are not negligible, that is, correlation between shares of part-time workers and women, share of fixed-term workers and average tenure, and process and product innovations. Regardless, this preliminary evidence leads us to perform a multicollinearity test after OLS regressions to exclude any possible ambiguity around this aspect.

TABLE 2, HERE

5.1 OLS estimates

Table 3 presents OLS estimates for the whole economy. These results are obtained by controlling for firm characteristics (capital intensity, size, geographical location, innovation and internationalization strategies) and other characteristics that concern labour relations and the workforce (unionization, fixed bonuses, percentages of fixed-term and part-time contracts, composition by gender, job tenure, training). This high number of covariates does not create multicollinearity problems, as the variance inflation factors test signals (see Table A.2 in the Appendix)[xiv].

TABLE 3, HERE

Our results show that the regression coefficients associated with the dummy variable CPRP are significant at the 1% level for TFP and labour productivity. These estimates suggest that the adoption of collective wage incentives (CPRP=1) is associated with an increase in TFP of 4.5% and with an even greater increase in labour productivity of 7.5%.

As expected, innovation and foreign competition appear to be drivers of TFP and labour productivity, although at different significance levels (Melitz 2003). The results for workforce characteristics are more articulated. The adoption of fixed-term contracts is negatively and significantly associated with labour productivity, although not with TFP, whereas part-time contracts appear to exert negative effects on both efficiency indicators (TFP and labour productivity). This association could be related to a general lower commitment on the part of part-time workers, which starts to exert a negative influence on overall firm efficiency when the share of part-time workers on total employment increases. It is worth noting that other workforce, firm and institutional characteristics, such as tenure, training, unions and the use of fixed bonuses (EGR), appear in our specification as poor determinants of economic performance.

Table 4 offers additional results for sector-specific estimates. To make the comparison easier, we report the previous results for the whole sample in the first column. The results obtained reveal heterogeneous findings. OLS estimates indicate that the CPRP coefficient is positive and significant (although only at the 10% level) in L&M_Tech for TFP estimates and in KISs and LKISs for labour productivity.

Note that these results are all obtained after taking into account the whole set of control variables mentioned above (firms' strategies and characteristics) and after including sector (2_digits NACEce Rev.2 sectors) and regional (NUTS1) dummies.

From these preliminary results, we observe that no clear sectoral patterns emerge. In particular, in the descriptive statistics, we have observed a high percentage of firms implementing CPRP in the H&M_tech sectors; however, they do not appear to be the drivers of the overall positive and significant impact that this incentive pay scheme has at the aggregate level for the whole set of Italian firms. Indeed, it is within the L&M_Tech and service sectors (both KISs and LKISs) that we find positive and significant associations of CRPP with the outcome variables.

However, OLS estimates should be considered with caution and only as explorative investigations due to their potential biases relying on self-selection problems and the non-random assignment of CPRP. This problem is taken into account by adopting inverse probability weighting with regression adjustment (IPWRA).

TABLE 4, HERE

5.2 Inverse probability weighting with regression adjustment estimates

As discussed in section 4, the IPWRA method works within a counterfactual framework in which we estimate the gap between the average performances of firms adopting CPRP and the average performance the same firms would have achieved by not adopting CPRP (that is, the average treatment effect on the treated CPRP_ATET). In other words, we solve the missing data problem of firms for which we only observe one condition (adopting CPRP) by estimating their counterfactual (POMs, CPRP_Pot_Outcomes), which is the result obtained with no CPRP. By relying on the *overlap assumption,* we use the control group (CPRP=0) to estimate the CPRP_Pot_Outcomes for the treated group.

Because IPWRA combines a parametric method (RA) with a propensity score method (inverse probability weighting, IPW), in the Appendix (Table A.3), we also report the probabilities of treatment (adoption of CPRP) we estimated in the first step. The first step results tell us that many covariates influence the probability of CPRP adoption and that they should be taken into account by means of inverse probability weighting. In particular, larger size, unions and training positively influence the probability of CPRP.

As already performed for Table 4, in the second step of IPWRA estimations (see Table 5), we concentrate on the key results (CPRP_ATET and CPRP_Pot_Outcomes in this case) and omit all findings referring to covariates[xv].

TABLE 5, HERE

For the whole sample, IPWRA estimates of Table 5 confirm the previous OLS findings and suggest that our key explanatory variable CPRP shows a positive and significant impact at the 1% and 5% level of significance on both indicators of efficiency, TFP and labour productivity, respectively. More precisely, CPRP_ATET is 3.5% for TFP and 6.2% for labour productivity. This means that if treated firms had not implemented CPRP schemes, their logTFP would be 0.073 (1.07 in levels) and their log labour productivity would be 11.007 (60,295 euros 2010, in levels) (as shown by the CPRP_Pot_Outcomes, reported in Table 5). Instead, by implementing CPRP, Italian firms raised their log TFP by 3.5% and their labour productivity by 6.2%. These improvements are slightly lower than those reported by the OLS estimations (4.5% and 7.5% for TFP and labour productivity, respectively) and confirm that a slight upward bias affects OLS results. The unbiased values we obtain with the IPWRA method show an order of magnitude close to those found in related international literature (see, for instance, Gielen et al. 2010; Kato et al. 2012). Particularly if we restrict the comparison to similar studies focusing on Italy, the overall positive impact of CPRP on labour productivity that we find with the IPWRA estimator (i.e., 6.2%) better approaches the 5% impact that Lucifora and Origo (2015) found.

The case of sector-specific estimates seems to confirm previous results but also reveals new significant heterogeneities. First, we have confirmation of a causal effect on TFP and labour productivity only for KIS industries. For the other sectors, no significant results are obtained. One rationale behind this result might be that collective wage incentives, such as CPRP, fuel teamwork, interactive learning, and workers' commitment to cooperation and thereby reveal a strategic role in developing and integrating knowledge and workers' capabilities (Laursen and Mahnke 2001).

According to the OECD (2006), the effective management of human resources in KISs is based on forming multi-disciplinary research teams that broaden their own knowledge base by selling solutions to other firms. For example, in the software industry, new product ideas are often obtained by engineering and marketing departments that must collaborate to interpret feedback originating from customers and to offer them suitable solutions. These solutions emerge from daily work in time-restricted project groups and in contexts of high uncertainty that affect their final layout. In contrast, the multidimensional character of innovative activities is much less developed in H&M_Tech manufacturing, where sources of innovation reside within unique, specialized R&D departments, and innovation itself, despite the high uncertainty, is the outcome of specific research processes and technological trajectories (Gotsch and Hipp 2012). In addition, KISs are distinctly characterized by the substantial contribution of organizational change, much more so than manufacturing, as also found from the international input-output data of Peneder, Kaniovsk and Dachs (2003) and in studies by the European Commission (2012). All these reasons suggest that collective incentive payments could be more binding in KISs, where the need to favour personnel connections and to adequately establish collective problem-solving processes is more important.

5.3 Robustness check

As observed in section 4, we are not completely sure that correcting for *selection on observables* by means of the IPWRA estimator is sufficient. For example, if innate manager capabilities strongly affect CPRP implementation and are not adequately captured by covariates such as firm size, multinational enterprise or innovation capabilities, the random assignment of CPRP is not restored when we use the IPWRA method.

Therefore, we perform an ATET estimation using instrumental variables (IV_ATET) and test the joint significance of estimated correlations between *unobservables* and error terms in both potential-outcome models (CPRP=1 and CPRP=0) of equations 1 and 2.

As discussed in section 3.1, the set of excluded instruments includes a variable not used in the previous econometric analysis, that is, the past ability of the firm to pay (average ROS over the 2007-2010 period), and four currently used variables that can be considered instruments, as they proved to not be correlated with TFP or labour productivity (see Table 3), whereas they resulted in important determinants of CPRP (see Table A.3, in the Appendix). These four covariates, which are added to past profitability in the set of excluded instruments, are *unions*, *tenure*, *training* and fixed bonus (*EGR*)[xvi].

The results for the IV_ATET and endogeneity tests are reported in Table A.4 (in the Appendix). Nearly all coefficients of CPRP_IV_ATET, both in the whole sample and across sectors, are not significant because the standard errors are much higher than those obtained with the IPWRA estimator (see Table 5). The significance of the correlation between *unobservables* and the outcome models is very weak and only detected for the counterfactual model (outcome mod.0). The joint significance of the two correlations, that is, the endogeneity test (last row of Table A.4), tell us that we cannot reject the null hypothesis that the treatment and outcome *unobservables* are not correlated. According to Wooldridge (2010), if there is no *selection on unobservables*, IPWRA remains a more reliable estimator due to its higher consistency and efficiency[xvii].

6. Conclusions

Focusing on a specific HRM practice represented by collective wage incentives, such as CPRP, we have found that this type of reward system is more efficacious in terms of TFP and labour productivity when adopted in KISs.

The peculiarities of KISs call to the forefront the abilities of firms operating in these sectors to convert skills and knowledge held by their human capital into intellectual capital and expertise, for instance, by developing skills to match demand and finding specific solutions that provide value for their clients. These skills may be more easily obtained under a high degree of decentralization and the application of HRM practices that involve teamwork, the delegation of decision rights and performance-based payments.

Our result is aligned with evidence offered by the OECD report (OECD 2006), which shows that in some KIS sectors, such as software services, cooperative relations between different departments of the same company (i.e., the engineering and marketing departments in the software computer case) are key factors in firm innovation and success. Furthermore, in services, innovation may be driven not so much by technology but, above all, as a response to customer needs, and when a firm learns from its customers, 'it is likely that learning will be embedded in individuals within the firm', as has been found in a number of sectoral KIS studies (see the OECD report 2006). In this case, managerial practices and incentives also play a strategic role in promoting the acquisition of skills, team production, knowledge sharing and creativity.

The institutional peculiarities of the labour market matter for explaining the role of wage incentives on knowledge creation and sharing and, through these channels, on labour efficiency. The Italian economy is a notable case study because it is characterized by wage setting rules quite similar to those of many other European countries, where firm-level wage contracts supplement industry-level wage setting. However, in Italy, where there are no statutory minimum wages, wage setting is based on sector-wide agreements that set the 'base wages', whereas firm-level negotiations have a limited influence, especially in service sectors. A wider space for firm-level contracts and CPRP would benefit productivity growth and innovation. These agreements could be particularly valuable because the Italian service sectors, since 2010, have displayed declining trends, especially in professional, scientific, and business technical support activities (Bugamelli and Lotti 2018).

Finally, note that Italian institutional peculiarities have not permitted determination of whether group and individual bonuses may be used as complementary practices to induce knowledge sharing *and* the generation of new and useful ideas. Hence, it would be useful if more research could be conducted based on the experiences of other countries where firm-level agreements and hybrid wage incentives, such as individual and collective incentives, are more diffused. These contexts could allow recognition of individual creativity and verify the role of group and individual rewards and their importance in KISs.

In more general terms, we can draw from this study some valuable lessons for policy and management choices. Peneder, Kaniovsk and Dachs (2003) document from international input-output data the rise of knowledge-based services as the most dynamic component and the new engine of growth. Indeed, as also recalled by the European Commission (2009, 19), KISs play a role in 'conceptualizing and disseminating tacit forms of production and market knowledge, selecting good practice information with regard to different competence areas'. The European Commission also signals that, to date, KISs have hardly benefited from public measures aimed at sustaining their innovation activities. Indeed, the latter mainly concentrated on technological innovation and overlooked those activities that best characterize KISs, such as organizational and marketing innovations (see European Commission 2012, Chapter 4). Thus, implementing performance-based rewards might be an efficient tool to stimulate those organizational innovations that, in turn, boost firms' efficiency and shorten the distance to the Lisbon Strategy targets.

TABLES AND FIGURES

Table 1 Descriptive statistics

	Whole Sample		H&M_Tech		L&M_Tech		KISs		LKISs		Other	
Variable	**Mean**	**CV**	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
TFP (levels)	**1.05**	**0.28**	1.21	0.23	0.97	0.16	1.12	0.29	0.96	0.33	1.20	0.23
LP (Euros)	**62,851**	**0.74**	74,331	0.65	60,470	0.61	63,924	0.82	58,985	0.81	62,046	0.80
CPRP	**8.84**		13.77		11.44		6.93		6.16		6.61	
Log_K_L	**9.81**	**0.19**	10.34	0.12	10.58	0.13	8.99	0.22	9.24	0.23	10.38	0.16
Fixed_Term(%)	**12.59**	**1.41**	6.59	1.14	7.92	1.23	20.66	1.25	13.73	1.29	10.96	1.09
Part-Time(%)	**15.45**	**1.50**	5.67	1.24	6.21	1.40	21.55	1.18	27.97	1.11	5.92	1.59
Women(%)	**36.01**	**0.71**	27.43	0.68	30.50	0.75	47.19	0.53	44.06	0.62	13.24	0.74
Tenure (years)	**9.02**	**1.75**	10.48	2.29	10.97	2.04	7.56	1.50	7.80	1.78	8.33	1.28
Training(%)	**24.58**		16.06		19.33		30.71		23.96		38.10	
Unions(%)	**48.37**		57.74		59.57		32.78		46.50		47.09	
EGR(%)	**18.02**		14.72		18.71		17.99		18.18		20.11	
Inno_prod(%)	**43.73**		74.19		54.79		41.37		25.85		24.60	
Inno_proc(%)	**40.40**		58.32		54.26		31.23		28.79		30.16	
Export(%)	**48.10**		85.28		78.46		28.23		27.18		15.34	
MNE(%)	**4.96**		8.99		4.43		4.45		5.02		2.12	
Size(% 10-49)	**41.73**		39.96		38.56		55.64		31.25		47.35	
Size(% 50-250)	**36.13**		34.61		43.53		30.40		34.19		36.24	
Size(% >250)	**22.14**		25.43		17.91		13.96		34.56		16.40	
North_West(%)	**31.76**		38.05		31.21		33.51		29.17		27.51	
North_East(%)	**26.41**		27.72		27.57		28.13		23.77		24.07	
Centre(%)	**20.41**		16.83		21.45		19.86		20.93		22.22	
South(%)	**13.47**		12.81		13.48		11.27		15.06		15.61	
Islands(%)	**7.95**		4.59		6.29		7.24		11.08		10.58	
Ros_lagged (%)	**5.83**		10.34		9.53		13.51		-5.49		0.50	
Obs	**3806**		498		1082		889		986		351	

Note: The coefficient of variation (CV) is reported for only firm-level continuous variables.

Table 2 Correlation matrix of variables used in the empirical analysis

	TFP	Labour Product.	CPRP	Log_ K_L	Fixed_ Term	Part-Time	Women	Training	Tenure	Unions	EGR	Inno_ prod	Inno_ proc	Export	MNE	Lagged_ ROS
TFP	1.00															
Labour Product.	0.49	1.00														
CPRP	0.08	0.11	1.00													
Log_K_L	0.18	0.37	0.12	1.00												
Fixed_Term	-0.16	-0.21	-0.08	-0.15	1.00											
Part-Time	-0.35	-0.45	-0.09	-0.36	0.18	1.00										
Women	-0.16	-0.20	-0.07	-0.28	0.11	0.50	1.00									
Training	0.06	0.05	0.05	0.01	-0.01	-0.03	-0.02	1.00								
Tenure	0.11	0.12	0.16	0.24	-0.43	-0.23	-0.11	-0.01	1.00							
Unions	0.00	0.07	0.27	0.14	-0.24	-0.08	-0.12	0.05	0.31	1.00						
EGR	0.03	0.04	-0.06	-0.02	-0.03	-0.01	0.02	-0.03	-0.02	-0.07	1.00					
Inno_prod	0.11	0.15	0.08	0.12	-0.12	-0.13	-0.04	0.02	0.09	0.10	0.00	1.00				
Inno_proc	0.08	0.13	0.07	0.14	-0.13	-0.12	-0.07	0.05	0.08	0.13	0.02	0.44	1.00			
Export	0.14	0.24	0.10	0.22	-0.12	-0.29	-0.11	-0.05	0.18	0.13	0.01	0.29	0.21	1.00		
MNE	0.07	0.13	0.05	0.00	-0.02	-0.04	0.01	0.07	0.04	0.11	-0.02	0.05	0.04	0.10	1.00	
ROS_ 2007-2010	0.00	0.01	0.04	0.00	0.00	0.01	-0.01	0.00	0.01	0.01	-0.01	0.00	0.00	-0.01	0.00	1.00

Table 3 Effetcs of collective performance related pay on firm's performances (OLS)

Dep. Vars	TFP_log	Labour Productivity_log
Explanatory vars.		
CPRP	0.045***	0.075***
	(0.014)	(0.028)
Log_K_L		0.094***
		(0.006)
Fixed_Term	0.000	-0.004***
	(0.000)	(0.001)
Part-Time	-0.003***	-0.009***
	(0.000)	(0.000)
Women	-0.001***	-0.001**
	(0.000)	(0.000)
Training	-0.004	0.014
	(0.007)	(0.018)
Tenure	-0.000	-0.008***
	(0.001)	(0.002)
Unions	-0.006	-0.024
	(0.008)	(0.019)
EGR	0.008	0.019
	(0.007)	(0.020)
Inno_prod	0.026***	0.034*
	(0.007)	(0.018)
Inno_proc	0.008	0.046***
	(0.007)	(0.018)
Export	0.051***	0.132***
	(0.007)	(0.021)
MNE	0.061***	0.286***
	(0.015)	(0.042)
Size Dummies	yes	yes
Sector Dummies	yes	yes
Geo-dummies	yes	yes
Constant	0.430***	3.276***
	(0.035)	(0.083)
Observations	3,806	3,806
R-squared	0.590	0.409

Note: Bootstrap (for TFP) and robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Effects of performance related pay on firm's performances in different Technology/Knowledge intensive sectors (OLS)

	Dep.Var: TFP_log					
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP	0.045***	-0.016	0.020*	0.035	0.021	0.041
	(0.014)	(0.023)	(0.011)	(0.027)	(0.022)	(0.032)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,806	498	1,082	889	986	351
R-squared	0.591	0.388	0.508	0.701	0.687	0.767
	Dep.Var: Labour Productivity_log					
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP	0.075***	-0.059	0.071	0.125**	0.112*	-0.087
	(0.028)	(0.067)	(0.046)	(0.063)	(0.067)	(0.102)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,806	498	1,082	889	986	351
R-squared	0.409	0.222	0.230	0.470	0.606	0.380

Note: Other includes Mining and Quarring, Construction and Utilities. Bootstrap (for TFP) and robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5 Effects of performance related pay on firm's performances (Inverse Probability Weighted Regression Adjustement, IPWRA)

	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
Dep.Var: TFP_log						
CPRP_ATET	0.035***	-0.009	0.017	0.057**	0.024	0.029
	(0.009)	(0.026)	(0.011)	(0.025)	(0.022)	(0.028)
CPRP_Pot.Outcomes	0.073***	0.206***	0.005	0.152***	-0.022	0.240***
	(0.010)	(0.021)	(0.009)	(0.029)	(0.030)	(0.033)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,806	498	1,082	889	986	351
Dep.Var: Labour Productivity_log						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP_ATET	0.062**	-0.053	0.067	0.125*	0.107	-0.045
	(0.029)	(0.074)	(0.048)	(0.067)	(0.069)	(0.125)
CPRP_Pot.Outcomes	11.007***	11.144***	10.964***	11.085***	10.928***	10.940***
	(0.022)	(0.042)	(0.034)	(0.069)	(0.054)	(0.125)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,806	498	1,082	889	986	351

Note: Other includes Mining and Quarring, Construction and Utilities. Bootstrap (for TFP) and robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

FIGURES

Figure 1 Firms with targets related to CPRP across technology and knowledge intensity sectors

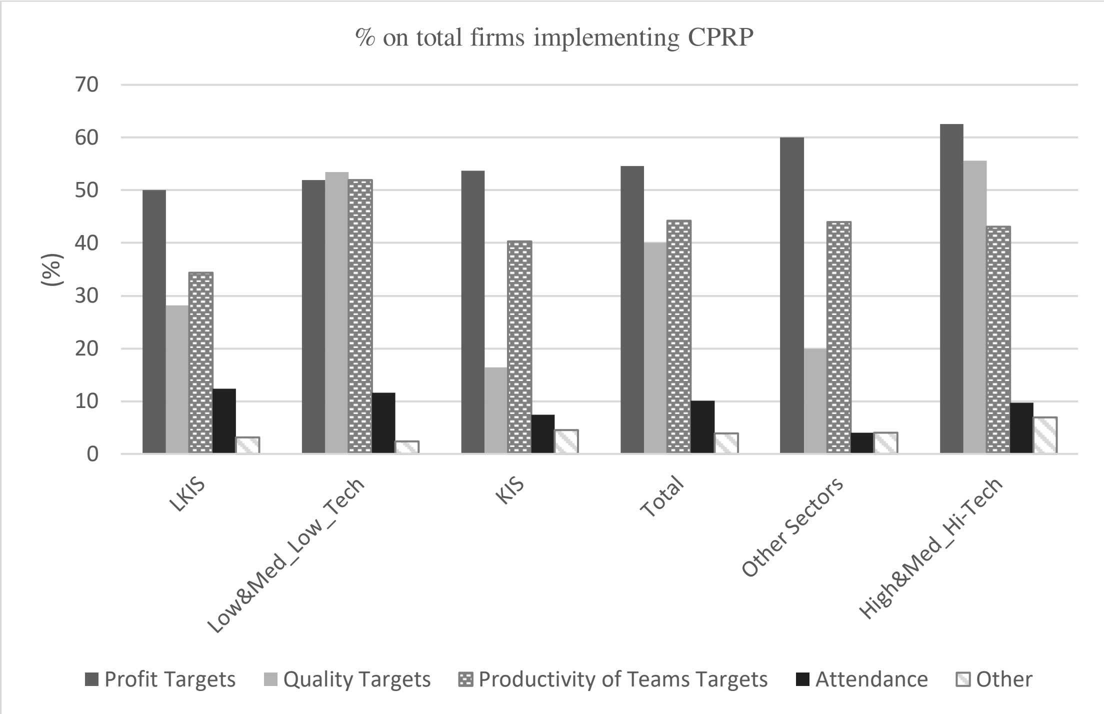
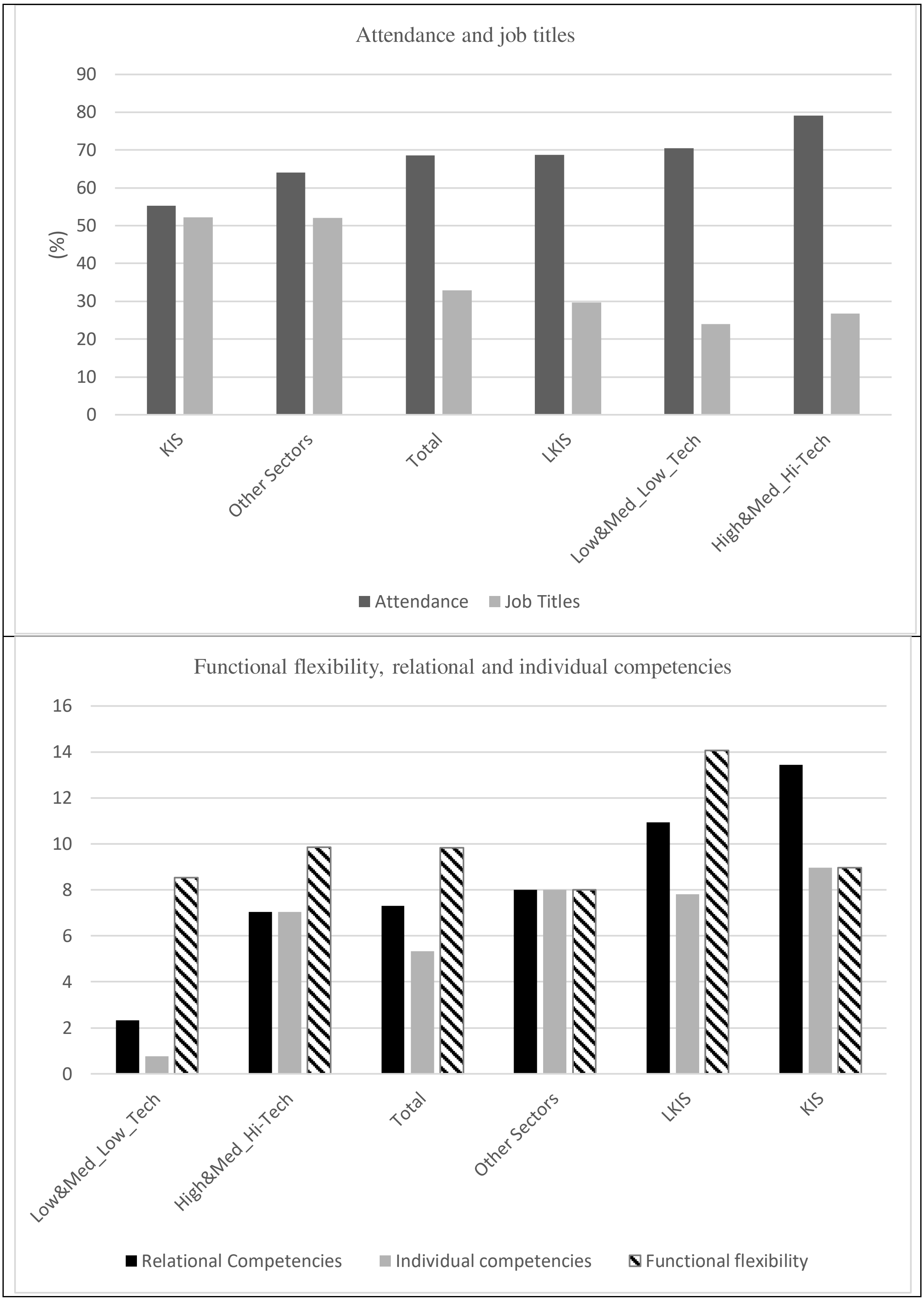


Figure 2 Firms with criteria for CPRP distribution across technology and knowledge intensity sectors (% on total firms implementing CPRP)



APPENDIX

Table A.1 Production function for firm level TFP, 2007-2014 (GMM_SYS)

Dep.Var	**Log (Value Added/Labour)**
Log_K_L	0.050***
	(0.018)
Year Dummies	yes
Sector Dummies	yes
Constant	10.644***
	(0.216)
Observations	62,368
Number of Firms	9,360
Number of instruments	98
Arellano-Bond test for AR1 (p_value)	0.000
Arellano-Bond test for AR1 (p_value)	0.870
Hansen Test of overid. restrictions (p-value)	0.152

Note: *** p<0.01, ** p<0.05, * p<0.10.

Table A.2 Multicollinearity Test

Variable	**VIF**	**1/VIF**	**Variable**	**VIF**	**1/VIF**
CPRP	1.12	0.89	**Sectors**		
Log_K_L	1.45	0.69	Mining & Quarring	1.03	0.97
Fixed_Term	1.42	0.71	Electricity & Gas	1.04	0.96
Part-Time	1.84	0.54	Water Supply	1.23	0.81
Women	1.79	0.56	Construction	1.24	0.80
Training	1.08	0.93	Wholesale & Retail Trade	1.34	0.74
Tenure (years)	1.45	0.69	Transportation	1.26	0.79
Unions	1.55	0.64	Accomodation & Food Serv	1.3	0.77
EGR	1.05	0.96	Information & Comm.	1.24	0.81
Inno_prod	1.35	0.74	Finance	1.05	0.95
Inno_proc	1.28	0.78	Real Estate	1.03	0.97
Export	1.63	0.61	Professional & Sc. Activities	1.27	0.79
MNE	1.07	0.94	Administrative & Service Act	1.7	0.59
Size			Education	1.14	0.88
Size (50-250)	1.4	0.71	Human Health	1.28	0.78
Size (>250)	1.77	0.56	Arts & Entert.	1.4	0.71
Regions			Other Services	1.13	0.88
North_East	1.37	0.73			
Centre	1.34	0.75			
South	1.33	0.75	**Mean VIF**	**1.32**	
Islands	1.24	0.81	***Mean VIF_TFPequation***	***1.31***	

Note: the variance inflation factors test refers to the OLS regression reported in Table 3 (labour productivity equation). The mean VIF result is also reported for TFP equation, where only Log_K_L is omitted. As for size, regional and sectoral dummies, small firms (10-49), North_West and Manufacturing are the categories necessarily excluded from the regression, respectively.

Table A.3 Estimation of probabilities of treatment: first stage of IPWRA estimation (probit model)

2nd stage Dep. Vars	**TFP_log**	**Labour Productivity_Log**
1st stage Dep.Vars	**CPRP**	**CPRP**
Log_K_L		0.177***
		(0.046)
Fixed_Term	0.013**	0.017***
	(0.006)	(0.006)
Part-Time	-0.012**	-0.008
	(0.005)	(0.006)
Women	-0.003	-0.004
	(0.004)	(0.004)
Training	0.425***	0.468***
	(0.138)	(0.146)
Tenure	0.040***	0.039***
	(0.011)	(0.012)
Unions	2.056***	2.021***
	(0.203)	(0.213)
EGR	-0.378**	-0.279
	(0.188)	(0.195)
Inno_prod	0.054	0.034
	(0.137)	(0.144)
Inno_proc	-0.212	-0.270*
	(0.134)	(0.142)
Export	-0.078	-0.028
	(0.181)	(0.185)
MNE	-0.297	-0.138
	(0.245)	(0.246)
Size(50-250)	0.592***	0.603***
	(0.179)	(0.189)
Size(>250)	0.849***	0.800***
	(0.195)	(0.208)
Sector Dummies	yes	yes
Geo-dummies	yes	yes
Constant	-4.649***	-5.335***
	(0.792)	(0.829)
Observations	3,806	3,806

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.4 Effects of performance related pay on firm's performances (Average Treatment Effects on Treated using Instrumental Variables)

	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
Dep.Var: TFP_log						
CPRP_IV_ATET	0.064	0.209**	0.070	-0.144	0.016	0.164**
	(0.046)	(0.096)	(0.043)	(0.102)	(0.129)	(0.073)
CPRP_Pot.Outcomes	0.044	-0.012	-0.048	0.353***	-0.014	0.123
	(0.045)	(0.095)	(0.043)	(0.106)	(0.128)	(0.083)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,803	498	1,082	889	984	350
Correlations between unobservables	-0.022	-0.220**	-0.052	0.182	0.009	-0.121
and outcome mod.0	(0.470)	(0.100)	(0.044)	(0.110)	(0.132)	(0.076)
Correlations between unobservables	0.206	-0.176	0.264	-0.536	-0.500	-0.547
and outcome mod.1	(0.181)	(0.346)	(0.199)	(0.374)	(0.350)	(0.691)
Endogeneity Test (p-value) H0: treatment and outcome *unobservables* are uncorrelated	0.462	0.106	0.258	0.108	0.360	0.201
Dep.Var: Labour Productivity_log						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP_IV_ATET	0.143	-0.413	-0.476	0.303	1.221	-2.504
	(0.141)	(0.257)	(0.400)	(0.295)	(0.100)	(3.550)
CPRP_Pot.Outcomes	10.926***	11.504***	11.507***	10.907***	9.813***	13.421***
	(0.135)	(0.244)	(0.218)	(0.279)	(0.345)	(3.555)
Control Variables	yes	yes	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes	yes	yes
Observations	3,803	498	1,082	889	984	350
Correlations between unobservables	-0.035	0.363	0.569**	-0.125	-1.082***	2.383
and outcome mod.0	(0.140)	(0.258)	(0.300)	(0.295)	(0.353)	(3.530)
Correlations between unobservables	0.158	0.280	1.054	-0.081	1.140	0.510
and outcome mod.1	(0.535)	(1.605)	(0.670)	(1.395)	(1.248)	(0.591)
Endogeneity Test (p-value) H0: treatment and outcome *unobservables* are uncorrelated	0.906	0.373	0.160	0.914	0.106	0.182

Note: Bootstrap (for TFP) and robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
3 observations dropped because they violate the overlapping assumption.

Table A.5 Average Treatment Effects on Treated using Instrumental Variables (Results for excluded instruments in the first-step probit)

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Dep.Var: CPRP						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
ROS_2007-2010	0.768**	-0.443	0.505	0.784**	1.552**	1.753*
	(0.318)	(0.483)	(0.590)	(0.350)	(0.646)	(1.090)
Unions	1.060***	1.257***	1.066***	1.010***	0.942***	-0.001
	(0.079)	(0.216)	(0.159)	(0.155)	(0.166)	(0.015)
EGR	-0.193**	-0.195	-0.299*	0.030	-0.034	-1.002**
	(0.092)	(0.231)	(0.160)	(0.187)	(0.188)	(0.463)
Training	0.218***	0.296	0.121	0.416***	0.167	0.358
	(0.069)	(0.194)	(0.131)	(0.140)	(0.150)	(0.262)
Tenure	0.028***	0.027	0.041***	0.002	0.032***	-0.026
	(0.005)	(0.017)	(0.010)	(0.013)	(0.012)	(0.020)
Constant	-2.467***	-2.291	-2.530***	-2.286***	-2.665***	-1.119
	(0.096)	(0.280)	(0.188)	(0.198)	(0.197)	(0.308)
Observations	3,803	498	1,082	889	984	350

3 observations dropped because they violate the overlapping assumption.

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[i]Wang et al. (2017) also demonstrated that firms with greater specificity in knowledge structure need to properly design the compensation structure to improve firm economic performance. They showed that specificity in firm knowledge assets is positively associated with the use of restricted stocks in CEO compensation to discourage CEO dismissals.

[ii] For aggregation of the manufacturing industry according to technological intensity and for aggregation of services by knowledge intensity, see Eurostat indicators on the high-tech industry and knowledge-intensive services, http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf.

iii Gibbs (2016) collects the different views of a group of leading economists in this area of research, such as Kevin Hallock (Cornell University), Edward Lazear (Stanford University), Kevin Murphy (USC), and Canice Prendergast (University of Chicago).

[iv] One channel that removes these uncooperative actions is accessed when *shared capitalism* and collective performance-related pay schemes are adopted in combination with other complementary HRM practices. However, in the present paper, the availability of data does not allow to control for the combined role of HRM practices.

[v] These activities have been grouped by Eurostat in the subset of knowledge-intensive business activities (KIBS) but are not considered separately from the other knowledge-intensive activities in our empirical analysis. From a thorough analysis of KIS, it clearly emerges that complex knowledge, teamwork and the need to share knowledge are widespread across all sectors included in KISs, as also documented by the case studies for different industries, such as healthcare and education, examined by the OECD report (2006).

[vi] Job titles (*livelli di inquadramento*) are defined by national industry-wide collective bargaining contracts, for which specific minimum wages apply. They are assigned according to different qualifications and skills of workers.

[vii] According to the SICA-LCS questionnaire firms can use more than one targets and criterion when they implement CPRP. In addition, data are collected for both cash variable compensation and employee share ownership plans, that involve employees participating in firm property rights. However, the second type of incentives are limited diffused in Italy and are not examined in this study. Finally, note that to avoid repetitions we use interchangeably terms such as collective bonuses and collective incentive pay schemes, although, from what we discussed above they are not exactly the same thing.

[viii] Unfortunately, the SICA-LCS survey does not provide similar information for individual incentives.

[ix] The return on sales is the ratio of gross operating margin on total sales.

[x]The Eurostat Hi-tech classification of industries is available at http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf. To avoid excessive asymmetries across the classes size, we had to collapse the original four classes (high-tech, med-high-tech; med-low tech, low-tech) into two ones.

[xi] It is worth noting that the values for TFP in levels are very close to those found in the related literature dealing with TFP estimation for Italian firms (Altomonte and Aquilante 2012; Aiello, Pupo and Ricotta 2014).

[xii] It must be remarked that we only have a binary variable for export (1 for an exporting firm, independent of the proportion of sales that come from selling abroad, and 0 otherwise). In addition, only firms with ten employees or more are in the sample.

[xiii] Thus, the new variable is the past profitability, that we only use as instrument. However, the set of excluded instruments also includes covariates such as unions, tenure and training that proved to be highly correlated with CPRP and not influencing economic performances in OLS and IPWRA specifications (see section 5).

[xiv] According to Chatterjee and Hadi (2012), the presence of multicollinearity relies on two rules of thumb, which are used to interpret the VIF test. Multicollinearity is signaled by the largest *VIF* (among variables) being larger than 10 and the *mean VIF* being considerably larger than 1 (above 5); Table A.2 shows that this is not true in our case.

[xv] These results are available upon request.

[xvi] It means that the specification in IV_ATET is slightly different from that we use in the OLS and IPWRA estimations. In the former, *unions*, *tenure*, *training* and *EGR* only enter the set of excluded instruments. Since the purpose of this robustness check is only to test the potential strong endogeneity of CPRP that is not corrected by the IPWRA method, we do not care about differences in the size of the CPRP_ATET coefficients of Table A.4 driven by differences in the model specification.

[xvii] We obtain this result despite the relevance detected in the instruments set. Table A.5, in the Appendix, reports findings for the first step probit, performed to calculate residuals $\hat{v}_i$. The five instruments (i.e., *ROS_2007-2010*, *unions*, *EGR*, *training* and *tenure*) are strong determinants of the treatment (CPRP) in the whole sample. Past profitability, unions and training remain highly significant drivers of CPRP adoption in KISs.