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

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ABSTRACT

Literature on collective performance-related pay (CPRP) has incompletely explored the heterogeneous role of this type of scheme across sectors. This paper is aimed at filling this gap. Theory suggests that in knowledge-intensive service sectors (KISs), where the intellectual nature of knowledge of the personnel is the major resource, firms cannot rely on standardization of this strategical input. In these contexts, the development of firms' dynamic capabilities strongly requires the organization and motivation of their key employees. For this reason, CPRP may be particularly effective in encouraging creation, utilization and sharing of local knowledge. Cross-sectional estimates obtained for a national sample of approximately 4,000 Italian firms for 2012 confirm this prediction and show the positive role of CPRP on performance of firms operating in KISs, more significantly than in other sectors. These results have been validated by adopting a treatment effect approach to solve the self-selection problem and correct potential biases due to non-randomized observations.

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

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1. Introduction

Studies focusing on the role of incentive pay schemes have gained ground in the last decades and documented significant heterogeneities within and across countries (Bryson et al. 2013). To explain these heterogeneities, a vast body of research has predominantly considered the different types of wage incentive schemes. For example, some authors analysed individual versus collective incentive payments (Kruse et al. 2010), while others investigated the adoption of these schemes implemented in isolation or as part of bundles of complementary human resource management practices (Milgrom and Roberts, 1995; Blasi et al., 2016).

In any case, most of the studies have considered wage incentive schemes as invariant to the type of sectoral activity, whereas the moderating effects of industrial environment are still limitedly explored, as observed by Chin et al. (2011). By contrast, a fruitful explanation of heterogeneous effects of wage practices may have as a premise the hypotheses advanced by the 'contingency approach' (Miles and Snow, 1984). In such approach, the main characteristics of each organization may be seen as the result of the main strategies adopted by the perception of the organization's environment. In this paper, in particular, we expect that the adoption of wage incentives is more effective in sectors characterized by high degrees of knowledge intensity. Indeed, organizational competences, intellectual capital and socialization of tacit knowledge among employees are strategical tools (Nahapiet and Ghoshal, 1998), and the reward system may be designed to encourage creation, sharing and utilization of this local knowledge *(*Bartol and Srivastava, 2002*;* Laursen, 2002). Furthermore, as posed by organizational theory, all these activities related to knowledge are characterized by higher degrees of strategic uncertainty (Laursen, 2002), and in contexts of uncertainty, firms *"*delegate responsibility to workers but, to constrain their discretion, base compensation on observed output" (Prendergast, 2000, p. 1071).

A case in point is represented by knowledge-intensive services (KISs), where due "to the intangible nature of services, and especially new services, the level of uncertainty and information asymmetries is quite high" (EU Commission, 2012, p. 33). In addition, in KISs most work is of an intellectual nature, and personnel knowledge is the major resource (Alvesson, 2000; Starbuck, 1992). We thus expect that in KISs management of human resources has a significant role and that output-based collective rewards are particularly efficacious in these highly labour intensive contexts, as these pay schemes encourage and reward knowledge creation and innovation and activate information sharing among co-workers.

Knowledge intensive services (KISs) represent a significant share of tertiary activities and, as countries grow, an increasing share of the whole economies in GDP terms (EU Commission, 2012). The demand for knowledge-intensive services also translates into higher rates of growth of qualified employment with respect to other activities (Kox and Rubalcaba, 2007; EU Commission, 2012). Furthermore, the potential role of KISs in disseminating tacit forms of knowledge may help other sectors to reach the efficiency frontier with a clear evidence of knowledge spill-over effects (Camacho and Rodriguez, 2007). On the other hand, the overall KISs performance in the EU has been found largely responsible for the labour productivity growth distance of European economies with respect to the US (Inklaar et al. 2008, p. 142). Indeed, the slow and declining labour productivity growth in services of EU countries, particularly in the Italian case, is still an unanswered question in the ongoing debate.

Starting from these considerations, this paper aims at analysing the relationship between collective performance-related pay (CPRP) and firms' performances (labour and total factor productivity, returns on sales, ROS and returns on assets, ROA) for the whole Italian economy and different sectors, grouped by the degree of technological and knowledge intensity (Eurostat classification)[1]. 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 collective wage incentives reveal a distinctive and additional driver of productivity and profitability performances 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 performed 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).

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

In testing the CPRP and firms' performance relationship, we also take into account the potential self-selection problem, as firms' decisions to adopt 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).

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.

2. Literature review

2.1 Selected studies on collective performance-related pay

Collective wage bonuses that link pay to performance, such as collective performance-related pay (CPRP), constitute a commitment device to align worker and firm objectives and to 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, p.24).

However, on empirical grounds, these expected outcomes have been only partially confirmed, as a vast body of studies have shown considerable variations in the effects of CPRP on firm performance, quite often measured in terms of productivity gains (see Freeman, Blasi and Kruse, 2010, Bryson et al. 2013). One rationale behind these divergences could be that collective bonuses are not exempt from potential drawbacks (Ben-Ner, and Jones, 1995). The very fact that they are collective may induce employees to shirking and freeriding on the efforts of others, causing underperforming results in terms of firm productivity[2].

Innovation may be a moderator variable (Park and Kruse, 2016) under the hypothesis advanced in organizational theory that in innovative firms there is an increasing difficulty in programming worker jobs that involve low programmability (Banker et al. 1996). As recalled by Harden et al. (2010), in the principal-agent problem (Laffont and Martimort 2002), the owner has to delegate various tasks to the members of the firm who possess *private* information and it becomes strategical for agents to use their information to pursue profitable innovation for the owner (the principal). One of the purposes of collective incentives is thus creating cooperation and information sharing among co-workers that "is supportive of innovation efforts." (Harden et al. 2010, p. 232).

A further step is to verify these hypotheses for firms operating in knowledge-intensive sectors (KISs), i.e., those sectors where, rather than physical or financial capital, knowledge is the most important input of firms.

2.2 Knowledge intensive sectors

Organizational practices related to upgrading of human capital are important components of "dynamic capabilities", i.e., those "skills, procedures, organization and decision rules that firms utilize to create and capture value" (Teece, 2010, p. 680). In some sectoral activities, the main strategical resources, which are difficult to transfer and difficult to trade, are not only process know-how but also customer relationship and knowledge possessed by skilled employees. Here, dynamic capabilities involve a number of practices related to the attraction, retention and rewarding of these key employees (Laursen, and Foss, 2012). High Performance Work Organization (HPWO) *simultaneously* contribute to firm performance and to forming competencies, and the key competencies transform "a potential capacity for action into an actual capacity for action". (Leoni, 2012, p. 318).

[2] One channel that removes these uncooperative actions is obtained when *shared capitalism* and collective performance-related pay schemes are adopted in combination to 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.

A case in point is represented by those sectoral activities, such as KISs, where firms employ the highest shares of scientific personnel in comparison to the average of all sectors (see EU Commission, 2012). It is conceivable that for this type of activities, the development of dynamic capabilities based on continuous reconfiguration of internal resources, which allow firms to survive in a changing business environment, also require a number of management practices, such as flexible teams, limited hierarchy and compensation arrangements based on performance-based incentives (Teece, 2010).

Indeed, workers' capabilities and accumulation of knowledge have a central concern in Knowledge intensive sectors (KISs). As suggested by Starbuck (1992), 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, p.716)[3]

As previous mentioned, in KISs, the human factor and the intellectual capital have a central role, and the same criterion of classification adopted by Eurostat reflects this point. Indeed, an activity is classified as knowledge intensive if tertiary educated persons represent more than 33% of the total employment in that activity. Thus, previous literature has recognized, among the most important topics, the relevance in KISs of "filling knowledge gaps" instead of "job filling" (Brelade, 2000), as well as the strategical role of "continuous coaching" rather than routinized training (Smith and Rupp, 2004). This is also because, in KISs, the nature of innovation is often interactive, project-based and strongly given by the processes of adaption to clients' needs. As a natural consequence, innovation is related to competences acquired 'on the job' but with a high development component. In particular, in some KISs subsectors (computer and related activities, legal and technical services, advertising,

[3] An "expert" might be defined as "someone with formal education and experience equivalent to a doctoral degree, and a knowledge intensive firm in which such experts are at least one-third of the personnel" (Starbuck, p.716). Interestingly, the criterion of classification adopted by EUROSTAT is close to this suggestion, since an activity is classified as knowledge intensive if tertiary educated persons represent more than 33% of the total employment in that activity.

research and development)[4], cumulative learning arising from relationships among users and suppliers has a central concern.

Considering the personnel structure, as mentioned above, KISs employ higher shares of scientific personnel than the average of all classes of activities in almost EU economies, as highlighted by the CIS surveys (see EU, 2012, Figure 14, p. 24). This implies that in KISs, human resource management (HRM) play a strategical role in influencing organizational learning and knowledge creation (Swart and Kinnie 2003; Jørgensen et al. 2011). Furthermore, the higher percentages in KISs of professional employment, compared to firms in other sectors, require proper measures "to retain these valuable high-skilled professional employees, and prevent them from being poached by competitors" (Miozzo, Desyllas, Lee and Miles et al. 2016, p.1338).

2.3 HRM and collective wage incentives in knowledge intensive sectors

The contingency approach has been limitedly used to verify how performance practices are affected by structural variables such technology and market context, which have typified the different sectors (Godard, 2004). In addition, much of published research on this topic has been conducted for the manufacturing sector and less frequently explored the service sector, where the great majority of employees work, as noted by Guest et al. (2003). Indeed, notwithstanding the key role human capital has been found to play in professional service firms (Hitt et al., 2001), so far, limited attention has been devoted to HRM in knowledge intensive sectors. From the literature review of Majeed (2009), it emerged that the majority of available papers focused on the US and devoted scant attention to company performances. The remaining few studies conducted for European countries mainly focused on Denmark, Sweden and Spain (see, respectively, Laursen and Mahnke, 2001; Alvesson, 2000; Cabrera and Cabrera, 2005).

As underlined by Bartol and Srivastava (2002), knowledge and expertise is a source of power that may be limited by disclosure; thus, the lack of

[4]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.

motivation to transfer knowledge to colleagues (Szulanski, 1996) is a serious concern that requires well designed management systems to remedy this reluctance to share expertise, especially in cases of tacit knowledge, whose propagation calls for socialization and apprenticeship. Rewards schemes, contingent on firm outcomes that require knowledge sharing to be obtained, reduce workers' reluctance to share knowledge and mitigate uncooperative attitudes.

Notice that in KISs, as argued by Laursen (2002), 'performance ambiguity', i.e., a situation where inputs and outputs are not easily measured, is a serious concern, so that a high degree of 'goal incongruence', due to the fact that the members of the organization have only partially overlapping goals, call for a unified form that fits well with firms' specific needs (Laursen, 2002). The author also tested this hypothesis and found for a sample of Danish firms that HRM practices are more effective within knowledge-intensive industries in comparison to other sectoral activities.

A number of theoretical arguments were also offered by Laursen and Foss (2003), who suggested that many HRM practices are particularly effective when adopted to delegate problem-solving rights to the shop-floor and when decentralization gives right to access to relevant and tacit knowledge (see also Laursen and Foss, 2012). Additionally, the compensation schemes should not only recognize differences but also reward cooperation (Teece, 2010, p. 707). Among the various HRM practices, we thus expect that reward designs and team incentives may influence knowledge sharing among co-workers and thus, firm capabilities.

However, the use of pay-for-performance schemes imposes additional risks on agents and becomes costly to the owner in terms of higher wages. As also argued by Prendergast (2002), there is "a tenuous trade-off between risk and incentives". Indeed, when the environment in which the firm operates is uncertain and the activities in which workers *are* engaged or those in which the workers *should be* engaged are not known, the only way to constrain workers' discretion is by offering output-based pay, with the consequence that there is a positive link between contingent rewards and uncertainty. Following this reasoning, it can be argued that delegation of responsibility and contingent payments may be more effective in sectors such as knowledge-intensive activities that are intrinsically more uncertain than other sectors (Laursen, 2002).

All these considerations led us to hypothesize that in KISs a distinctive and additional positive effect of the implementation of collective pay incentives on firms' performances could be at work. Therefore, the following empirical analysis, after investigating an overall impact of CPRP on the Italian firms' performances, concentrates on the same relationship when moderators are high- and medium-high-tech industries, low- and medium-low-tech industries, knowledge intensive services (KISs) and less-knowledge intensive services (LKISs).

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[5].

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 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

[5]The cost paid for this enlargement in the control variable set is a remarkable reduction in the number of observations considered in the econometric analysis.

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. The SICA section provides information about the adoption of firm level bargaining, and each firm is asked whether a collective performance-related pay (CPRP) scheme has been adopted. Therefore, our key explanatory variable, CPRP, 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 wage setting in 2012. Additional information on the payment of the so called "guaranteed element of remuneration" (Elemento di Garanzia Retributivo), which is a fixed amount bonus established at the first-level of bargaining, is also gathered by 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, industry and geographical location).

According to the literature (Belot et al.2007), job tenure could influence the firms' 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 specify four different indicators for firm performance, which are our outcome variables. All these 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 economic or financial performances.

In addition to a standard labour productivity measure (the ratio of value added to employment), we estimated the total factor productivity (TFP) with the method explained in section 4. Only for this derived variable (TFP), we take into account inputs and outputs of the firm-level production function over the whole available 2007-2014 period, then we average residuals over 2013-2014.

As regards profitability, we use the return on assets (ROA, gross operating margin on total assets), and the return on sales (ROS, gross operating margin on sales). ROS and ROA are two indicators considered in the literature concerning the effects of human resource management practices (Park and Kruse, 2016) or in studies taking into account relationships between productivity and profitability across Italian firms (Bottazzi et al., 2010).

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)[6]; 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.

As we will see in the following sections, when we combine all four datasets in the econometric analysis, the number of observations decreases from more than 6,000 (maximum number of observations available for the LCS dataset) to approximately 4,000. 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. Notice that in our sample, the highest share of firms is recorded in L&M_Tech sectors (28.18%) and LKISs (25.54%), summing to more than fifty per cent of the

[6]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.

whole sample (54%). Firms in KISs are 22.62 %, while the lowest share is found in H&M_Tech, only 15%, approximately.

As expected, the most advanced sectors, H&M_Tech and KISs, although less represented, show the highest values for both indicators of efficiency, i.e., total factor productivity (TFP) and labour productivity[7]. In particular, for both indicators the highest values are recorded for H&M_Tech, (above the averages of the whole economy), followed by KISs. Interestingly, in terms of profitability (returns on sales and on assets), the ranking order is different. For the returns on sales (ROS), the highest values are registered in KISs, while H&M_Tech occupies only the second position. For the return on assets (ROA), both service industries (KISs and LKISs) record the highest values, likely reflecting the higher rents of firms operating in less tradable sectors, which are less exposed to competition from international market players. This hypothesis is also confirmed by the low percentages of exporting firms in KISs and LKISs (27.46 % and 27.68 %, respectively), below the higher values recorded in the other sectors (84.31% in H&M_Tech and 76.44 in L&M_Tech)[8].

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

In terms of enterprise dimension, we observe that KISs are predominantly characterized by small firms, more than manufacturing and more than LKISs. In particular, KISs shows the highest incidence of firms with less than 50 employees, as the share of firms in the class with 10-49 employees is more than fifty per cent (51.14%) of the whole sector, in comparison to a value of

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

[8] It must be remarked that we only have a binary variable for export (1 for exporting firm, independently on the proportion of sales that come from selling abroad and 0 otherwise).

only one third observed in LKISs. The small size of firms operating in KISs are also associated with the lowest values of unionization (34.51%), well below the figures found in the other sectors. Also remarkable, in KISs are the highest percentage of fixed-term contracts (21.62%), the lowest mean values of job tenure (7.89 years), and the highest share of women (around half of their workforce). Furthermore, firms operating in KISs are not particularly active in terms of outlays for innovation projects as firms involved in product and process innovation record percentages of 33.97% and 27.73%, well below the values found in both manufacturing industries. By contrast, the highest incidence of innovation is registered in H&M_Tech, where product and process innovation involve 71.64% and 60.82% of firms, respectively. However, it is remarkable that firms operating in KISs offer more opportunities to their employees in terms of training, showing the highest percentage of workers that benefit from training programs (30% of their workforce).

Finally, but most importantly for our analysis, the key variable CPRP, which captures the adoption of collective wage incentives, shows a limited diffusion in both service sectors, where these schemes are adopted only by 6.53% and 6.79% of firms in KISs and LKISs, respectively. By contrast, in manufacturing, the incidence of CPRP is higher (14.91% and 12,21%, in H&M_Tech and L&M_Tech, respectively).

4. Econometric method

As we mentioned above, we calculated all dependent variables (i.e., four different indicators of performance) as average for years 2013 and 2014. This allows us to make information on CPRP (reference year 2012) sufficiently lagged with respect to firm economic and financial performances. As regards productivity, we use labour productivity (value added to labour ratio) and total factor productivity (TFP). The latter is an estimated variable obtained with the 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 total factor productivity 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 and trained employees, average job tenure) and for firm characteristics (size, process and product innovations, export propensity). Moreover, $\boldsymbol{F}_i$ also includes dummies for institutional factors that vary across firms and could affect performances, 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'). The parameter μ_s denotes sector dummies, γ_j regional (NUTS1_level) dummies, and ε_i is the error term capturing the idiosyncratic component of TFP.

For the remaining three dependent variables, an OLS regression such as the one reported in equation 2 has been carried out:

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

where now FP_i is a generic term indicating firms' performance and includes both the partial productivity index, such as labour productivity, LP, i.e., ln $\left(\frac{VA}{L}\right)_i$, and two profitability indexes, i.e., returns on sales (ROS) and returns on assets (ROA). The number of firms is i= 1, …3,806 for labour productivity and i= 1, …4,052 for ROA and ROS. It is worth noting that in this case it makes sense to control for $ln\left(\frac{K}{L}\right)_i$, which is the (log of) physical capital per employee.

All other terms of equation 2 are exactly those we already 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, if they correspond to 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, LP, ROA or ROS), we can express the ignorability assumption as the following:

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

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 Inverse Probability Weighted Regression Adjustment (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, LP, ROA or ROS 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. Thus, the POM in this case is the average of the counterfactual performance predicted for firms adopting CPRP, i.e., the TFP, LP, ROA, ROS 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.

5. Estimation results

5.1 OLS Estimates

Table 2 presents OLS estimates for the whole economy. These results are obtained controlling for firm characteristics (capital intensity, size, geographical location, innovation and internationalization strategies) and other characteristics that concern labour relations and workforce (unionization, fixed bonuses, percentages of fixed-term and part-time contracts, composition by gender, job tenure, training).

Our results show that the regression coefficients associated to the dummy variable CPRP are significant at the 1 percent level for total factor productivity (TFP) and labour productivity. These estimates suggest that the adoption of collective wage incentives (CPRP=1) is associated to an increase of TFP of 4.5% and even to a higher increase of labour productivity of 7.5%. By contrast, the corresponding increases for ROS and ROA are not significant.

An increase in the capital-to-labour ratio gives a significant contribution to productivity growth. At the same time, a higher value of this indicator that increases with the capital employed moderates the value of ROA, defined as the ratio of enterprise annual earnings to its total assets.

As expected, innovation and foreign competition appear as drivers of TFP and of labour productivity, although at different significant levels (Melitz, 2003). Interestingly, we also have a confirmation that international competition emerges as a constraint on financial returns, ROS and ROA. This constraint is mainly due to higher pressures on competitive policies of sectors not sheltered from international trade, as well as to additional fixed costs of exporting (Melitz and Redding, 2015).

More articulated are the results for workforce characteristics and unionization. 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 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. The other side of the coin are the lower labour costs associated to part-time workers. This could explain the positive association we find between higher share of part-timers and profitability. Opposite findings on ROS and ROA are obtained for workers with higher job tenure, suggesting that some form of rivalry between returns to experienced workers and firm’s profit is probably at work (see, for instance, the estimates for the German case of Dustmann and Meghir, 2005).

Finally, as expected, we find that worker representations are associated with lower ROS and ROA, confirming evidence that union impact on profitability is negative (Brown and Medoff, 1978).

Table 3 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 ten per cent level) in L&M_Tech for total factor productivity estimates and in KISs and LKISs for labour productivity. For

ROS, OLS results suggest a positive association with CPRP (significant at the 1 per cent level) only in KISs and LKISs. By contrast, in both manufacturing sub-sectors, it seems that higher costs related to adoption of CPRP offset their benefits (see Chin et al. 2011), with non-significant effects on ROS.

Notice that all these results are obtained taking into account all control variables mentioned above (firms' strategies and characteristics) and by including sector (2_digits Nace Rev.2 sectors) and regional (NUTS1) dummies.

From these preliminary results, we observe that no clear sectoral patterns emerge. In particular, we observed a high percentage of firms implementing CPRP in the H&M_tech sectors, but they do not seem to be the drivers of the overall positive and significant impact that this incentive pay scheme has at the aggregate level for the whole Italian firms. Indeed, it is within service sectors (both KISs and LKISs) that we find positive and significant associations of CRP with the outcome variables (i.e., in two out of four performance indicators).

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

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 performances the same firms would have achieved by not adopting CPRP (that is the average treatment effect on the treated CPRP_ATET). In other terms, we solve the missing data problem of firms for which we only observe one condition (adopting CPRP), by estimating their counterfactual (potential outcome means, 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.

Since IPWRA combines a parametric method (regression adjustment, RA) with a propensity score method (inverse probability weighting, IPW), in the appendix (table A.2) 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 they should be taken into account by means of inverse probability weighting. Especially, larger size, unions and training positively influence the probability of CPRP.

As already performed for Table 3, in the second step of IPWRA estimations (see Table 4) we concentrate on the key results (CPRP_ATET and CPRP_Pot_Outcomes in this case) and omit all findings referring to covariates[9].

For the whole sample, IPWRA estimates of Table 4 confirm OLS previous findings and suggest, for the whole private economy, 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 would not have 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 4). Instead, by implementing CPRP, Italian firms raised their logTFP by 3.5% and their Labour Productivity by 6.2%. These improvements are a bit lower than those reported by OLS estimations (4.5% and 7.5% for TFP and labour productivity, respectively) and confirm that a slight upward bias affects OLS results. However, the unbiased values we obtain with the IPWRA method show an order of magnitude close to those found in related literature (see for instance, Gielen et al. 2010; Kato et al. 2012).

Interestingly, IPWRA seems to correct a downward bias for OLS estimations that refer to ROS. Indeed, within a treatment effect context, the CPRP impact on the return on sales is positive and significant (0.741 percentage points),

[9] These results are available upon request.

even though at a 10% level of significance. Probably, by restoring independence between ROS, CPRP and covariates such as unions (that negatively impact on the ROS), an overall positive effect of incentive pay on this profitability proxy emerges.

The case of sector-specific estimates seems to confirm previous results but also reveals new significant heterogeneities. First of all, we have a confirmation of a causal effect on TFP and labour productivity at the 1% level of significance only for KISs 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 team work, interactive learning, and workers' commitment in cooperation that reveal themselves as strategic to developing and integrating knowledge and workers' capabilities, i.e., those inputs that are the main sources of competitive advantage of firms operating in knowledge-intensive sectors (Laursen and Mahnke, 2001).

As regards profitability indicators, IPWRA estimations help us to discover different patterns when we break down the economy into separate sectors.

For ROS, the results reported in Table 4 confirm that CPRP is found to affect firm profitability in KISs. Despite the significance level remaining weak (10%), the magnitude of the coefficient raises to 1.878 percentage points, suggesting that a HRM practice such as CPRP that generates efficiency gains in a sector with a lower exposition to foreign competition such as KISs, translates into higher profit margins. A positive and significant coefficient is also obtained for the other service subsector, LKISs, where limited international competitive pressures do not exert a dampening effect on price strategy.

Interestingly, for ROA the only significant effect from IPWRA estimation is obtained in KISs (CPRP_ATET is 2.441 percentage points in this case), a result not found with OLS estimates. Again, if treated firms operating in KISs would not have adopted CPRC, their return on assets would be 12.946% (CPRP_Pot.Outcomes). Instead, by adopting this incentive pay, their ROA becomes 15.387%, that is, 2.441 more than the counterfactual one. Furthermore, in this case, IPWRA corrects for a downward bias probably caused by the fact that KISs firms implementing CPRP are also those with unions, the latter being a variable that negatively affects ROA. Once we robustly partial out unions and other covariates that depress profitability, the impact of CPRP becomes positive. However, this happens only in KISs sectors.

6. Conclusions

The increasing interest in service innovation, observed in the last two decades, is related to their changed role "from adapters of innovation stemming from the manufacturing sector to important players in the innovation process", as signalled by the EU Report (EU, 2012, p.5). These processes call to the forefront the abilities of firms operating in knowledge intensive sectors in converting skills and knowledge of their human capital into intellectual capital and expertise, for instance by developing skills to match demands and finding specific solutions that have value for their clients. These skills, as in the growing sector of software engineering (Swart and Kinnie, 2003), are the main source of firm competitive advantage. A related argument concerns local knowledge, as the discovery and utilization of knowledge, which is key for the innovation process, may be more easily obtained under a high degree of decentralization and application of HRM practices that involve team work, delegation of decision rights and performance-based payments (Laursen, 2002).

Focussing on a specific HRM practice represented by collective wage incentives, such as CPRP, we have found that this kind of reward system is more efficacious in terms of total factor productivity and labour productivity when adopted in knowledge intensive sectors.

Ours results, also supported by controls for biases in treatment assignment, suggest that especially in KISs, where one observes high importance of knowledge, skills and creativity, as well as a high consulting component (EU, 2012, p.5), a collective incentive system improves firms' performances, probably because it fosters knowledge creation and knowledge sharing.

This is a key issue, as KISs have the potential to become one among the main drivers of the aggregate economic growth in terms of employment, value added and labour productivity (Kox and Rubalcaba, 2007). As recalled by the EU Commission (2009, p. 19), KISs have a role in “conceptualizing and disseminating tacit forms of production and market knowledge, selecting good practice information with regard to different competence areas”. On the other hand, the EU Commission also signals that, so far, KISs hardly benefited from public measures aimed at sustaining their innovation activities. Indeed, the latter mainly concentrated on technological innovation and overlooked those activities that characterize KISs most, such as organizational and marketing innovations (see EU Commission, 2012, chapter 4). Thus, as suggested by our results, implementing CPRP 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.*

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Table 1 Descriptive statistics for all variables across different technological intensity sectors

	Whole Sample		H&M_Tech		L&M_Tech		KISs		LKISs		Other	
	Mean	**CV**	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
TFP	**1.07**	**0.27**	1.22	0.23	0.98	0.16	1.09	0.31	0.98	0.32	1.21	0.24
LP (Euros)	**65,952**	**0.74**	77,218	0.64	61,972	0.62	68,554	0.84	62,816	0.80	62,276	0.74
ROS	**10.89**	**0.75**	10.64	0.72	9.14	0.77	13.59	0.63	9.62	0.82	13.67	0.68
ROA	**12.25**	**0.74**	11.44	0.73	9.47	0.80	15.97	0.67	13.02	0.70	12.05	0.67
CPRP	**9.54**		14.91		12.21		6.53		6.79		7.69	
Log_K_L	**9.83**	**0.19**	10.35	0.12	10.61	0.13	8.92	0.22	9.24	0.22	10.34	0.16
Fixed_Term(%)	**11.99**	**1.43**	5.89	1.20	7.72	1.29	21.62	1.20	13.79	1.28	10.64	1.13
Part-Time(%)	**14.53**	**1.54**	5.26	1.29	6.58	1.52	22.74	1.21	26.50	1.14	5.36	1.60
Women(%)	**35.73**	**0.71**	27.01	0.68	30.29	0.75	49.11	0.54	43.75	0.62	13.72	0.76
Tenure (years)	**9.66**	**0.56**	11.32	0.43	11.53	0.45	7.89	0.67	8.23	0.62	9.04	0.57
Training(%)	**0.25**		0.22		0.20		0.30		0.24		0.38	
Unions(%)	**51.31**		65.01		60.20		34.51		49.07		49.04	
EGR(%)	**18.18**		14.72		19.13		15.63		19.54		18.27	
Inno_prod(%)	**43.34**		71.64		52.26		33.97		27.18		22.12	
Inno_proc(%)	**41.02**		60.82		52.72		27.73		29.48		27.72	
Export(%)	**48.76**		84.31		76.44		27.46		27.68		14.10	
MNE(%)	**4.36**		7.99		3.70		4.03		4.59		1.66	
Size(% 10-49)	**41.03**		34.98		38.89		53.14		31.15		52.03	
Size(% 50-250)	**32.96**		31.23		38.43		30.96		30.80		31.93	
Size(% >250)	**26.00**		33.79		22.68		15.90		38.05		16.05	
North_West(%)	**34.52**		41.52		32.47		35.23		33.24		27.56	
North_East(%)	**25.03**		27.10		27.18		25.20		23.08		23.56	
Centre(%)	**19.75**		14.52		20.10		20.96		20.27		22.44	
South(%)	**13.11**		12.48		13.64		12.01		13.42		15.22	
Islands(%)	**7.60**		4.39		6.62		6.59		9.99		11.22	
Obs	**6973**		1026		1965		1577		1781		624	

Table 2 Effetcs of performance related pay on firm's performances (OLS)

Dep. Vars	TFP_log	Labour Productivity_log	Profitability (ROS)	Profitability (ROA)
Explanatory vars.				
CPRP	0.045***	0.075***	0.644	0.572
	(0.014)	(0.028)	(0.414)	(0.421)
Log_K_L		0.094***	1.330***	-0.969***
		(0.006)	(0.084)	(0.085)
Fixed_Term	0.000	-0.004***	-0.002	-0.012
	(0.000)	(0.001)	(0.008)	(0.010)
Part-Time	-0.003***	-0.009***	0.014**	0.022**
	(0.000)	(0.000)	(0.007)	(0.009)
Women	-0.001***	-0.001**	-0.003	-0.011
	(0.000)	(0.000)	(0.006)	(0.007)
Training	-0.004	0.014	0.798***	1.072***
	(0.007)	(0.018)	(0.280)	(0.323)
Tenure	-0.000	-0.008***	-0.061**	-0.167***
	(0.001)	(0.002)	(0.026)	(0.028)
Unions	-0.006	-0.024	-0.637**	-1.425***
	(0.008)	(0.019)	(0.276)	(0.323)
EGR	0.008	0.019	-0.036	0.747**
	(0.007)	(0.020)	(0.286)	(0.349)
Inno_prod	0.026***	0.034*	-0.259	-0.201
	(0.007)	(0.018)	(0.272)	(0.306)
Inno_proc	0.008	0.046***	0.322	0.338
	(0.007)	(0.018)	(0.265)	(0.298)
Export	0.051***	0.132***	-1.011***	-0.619*
	(0.007)	(0.021)	(0.300)	(0.351)
MNE	0.061***	0.286***	0.095	1.157*
	(0.015)	(0.042)	(0.608)	(0.652)
Size Dummies	yes	yes	yes	yes
Sector Dummies	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes
Constant	0.430***	3.276***	1.023	24.162***
	(0.035)	(0.083)	(1.542)	(1.435)
Observations	3,806	3,806	4,052	4,052
R-squared	0.590	0.409	0.199	0.156

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

Table 3 Effects of performance related pay on firm's performances in different Technology/Knowledge intensive sectors (OLS)

	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
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
Dep.Var: Profitability (ROS)						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP	0.644	-1.312	-0.138	1.888*	1.845**	2.167
	(0.414)	(0.918)	(0.645)	(1.051)	(0.934)	(1.710)
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	4,052	523	1,128	967	1,056	378
R-squared	0.201	0.078	0.053	0.158	0.305	0.348
Dep.Var: Profitability (ROA)						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP	0.572	-1.028	0.127	2.009	1.463	-0.208
	(0.421)	(0.990)	(0.602)	(1.266)	(0.973)	(1.300)
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	0.384	0.506	0.699	0.686	0.767

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 4 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						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
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
Dep.Var: Profitability (ROS)						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP_ATET	0.741*	-1.115	0.277	1.878*	1.795*	1.517
	(0.427)	(0.967)	(0.687)	(1.130)	(0.936)	(1.671)
CPRP_Pot.Outcomes	10.958***	10.464***	8.555***	14.725***	10.680***	16.352***
	(0.293)	(0.607)	(0.368)	(0.701)	(0.777)	(1.613)
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	4,052	523	1,128	967	1,056	378
Dep.Var: Profitability (ROA)						
	Whole Sample	H&M_Tech	L&M_Tech	KISs	LKISs	Other
CPRP_ATET	0.549	-0.897	0.416	2.441**	1.209	0.503
	(0.424)	(1.000)	(0.629)	(1.205)	(0.999)	(1.485)
CPRP_Pot.Outcomes	10.540***	10.667***	7.975***	12.946***	12.225***	11.188***
	(0.238)	(0.600)	(0.338)	(0.801)	(0.552)	(1.055)
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	4,052	523	1,128	967	1,056	378

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 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<0.1

Table A.2 Estimation of probabilities of treatment: first stage of IPWRA estimation (probit model)

2nd stage Dep. Vars	**TFP_log**	**Hourly Labour Productivity**	**Profitability (ROS)**	**Profitability (ROA)**
1st stage Dep.Vars	**CPRP**	**CPRP**	**CPRP**	**CPRP**
Explanatory vars.				
Log_K_hour		0.177***		
		(0.046)		
Log_K_L			0.197***	0.197***
			(0.043)	(0.043)
Fixed_Term	0.013**	0.017***	0.015***	0.015***
	(0.006)	(0.006)	(0.005)	(0.005)
Part-Time	-0.012**	-0.008	-0.010**	-0.010**
	(0.005)	(0.006)	(0.005)	(0.005)
Women	-0.003	-0.004	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Training	0.425***	0.468***	0.413***	0.413***
	(0.138)	(0.146)	(0.137)	(0.137)
Tenure	0.040***	0.039***	0.036***	0.036***
	(0.011)	(0.012)	(0.011)	(0.011)
Unions	2.056***	2.021***	2.003***	2.003***
	(0.203)	(0.213)	(0.200)	(0.200)
EGR	-0.378**	-0.279	-0.366*	-0.366*
	(0.188)	(0.195)	(0.188)	(0.188)
Inno_prod	0.054	0.034	0.017	0.017
	(0.137)	(0.144)	(0.135)	(0.135)
Inno_proc	-0.212	-0.270*	-0.272**	-0.272**
	(0.134)	(0.142)	(0.132)	(0.132)
Export	-0.078	-0.028	-0.100	-0.100
	(0.181)	(0.185)	(0.173)	(0.173)
MNE	-0.297	-0.138	-0.272	-0.272
	(0.245)	(0.246)	(0.238)	(0.238)
Size(50-250)	0.592***	0.603***	0.671***	0.671***
	(0.179)	(0.189)	(0.178)	(0.178)
Size(>250)	0.849***	0.800***	0.933***	0.933***
	(0.195)	(0.208)	(0.194)	(0.194)
Sector Dummies	yes	yes	yes	yes
Geo-dummies	yes	yes	yes	yes
Constant	-4.649***	-5.335***	-6.880***	-6.880***
	(0.792)	(0.829)	(0.903)	(0.903)
Observations	3,806	3,420	4,052	4,052

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