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Working Paper

The Dynamics of Skills: Technology and Business Cycles

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The Dynamics of Skills:

Technology and Business Cycles

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Abstract

Building on studies on the impact of the Great Recession on the skill structure of employment (Card and Mas, 2016), this article investigates developments over the last business cycle (2002-2007 and 2007-2011) in 38 manufacturing and service industries of five major European countries (Germany, France, Spain, Italy and United Kingdom). We analyze how technology, education and wages have shaped the evolution of four professional groups - Managers, Clerks, Craft and Manual workers – defined on the basis of ISCO classes. During the upswing in manufacturing industries all professional groups except managers have experienced job losses, while new jobs in services have followed a pattern of growing skill polarization. Demand growth has a general positive effect across all skills; new products lead to job creation in the group of managers only; wage increases slow down job creation except in the lowest skill group. During the downswing large job losses are concentrated in the lowest skills and most relationships – including the role of demand and wages -break down; product innovation loses its positive impact on jobs while new processes drive restructuring and job destruction across all groups.

JEL classification: J23; J24; J21; O3

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1. Introduction

The Great Recession has led to important changes in the employment structure of advanced economies. The long term process of structural change from manufacturing to service industries has accelerated; the employment structure is becoming more polarized, with job creation concentrated at the top and the bottom of the skill range in services; technology's impact on skills is becoming more complex than previously anticipated. Moreover, such developments are the result of a break with the relationships that shaped the evolution of the skill structure in times of economic expansion, pointing to the need for a deeper investigation on how the business cycle influences the dynamics of skills. This article improves on current research in the following three directions.

First, we investigate the skill structure of employment considering four major professional groups - Managers, Clerks, Craft and Manual workers - based on the International Standard Classification of Occupations (ISCO). These groups offer an appropriate representation of the nature of occupations, the hierarchy of business functions, workers' levels of education and competences. This allows to move beyond simpler classifications based on high vs. low skills; high vs. low education; types of tasks.[1]

Second, we introduce a more detailed investigation of technology, with the distinction between product and process innovation, and between firms' strategies that search for technological competitiveness or for cost competitiveness (Pianta, 2001). The former are associated with the presence of higher skills, the introduction of new products and the search for new markets. Conversely, cost competitiveness strategies are less skill demanding as they focus on mechanization and restructuring processes, with a direct labor saving impact. While these strategies generally coexist in firms, at the industry level it is possible to identify the dominant technological pattern and its impact on productivity and employment growth. This analysis allows us to move beyond the approach - typical of current literature - that expects technology (and ICTs) to have a uniform impact on all firms, industries and economies.

Third, we show that the evolution of skills is not independent from the business cycles. After identifying the main drivers of the long term dynamics of jobs and skills – technology, demand, education and wages – we investigate separately the determinants of job changes in each professional group during the 2002-2007 upswing and the 2007-2011 downswing of the last business cycle. Our results – similarly to a recent literature (Card and Mas, 2016), find that standard relationships are disrupted during downswings.

The rest of the paper is organized as follows. In the next section we revise recent contributions from the literature, section 3 introduces the dataset and describes the evolution of skills in Europe focusing on professional groups and the effects of cycles. In section 4 we present the econometric strategy used in the empirical investigation. Section 5 presents the main results; section 6 concludes.

2. The state of the art

Job changes have been investigated under different approaches, exploring absolute changes in jobs and the relative composition of skills. Among the main drivers of job changes, a large

[1] The ISCO classification has been widely adopted in the empirical literature to study employment dynamics by skill (among others, see Hollanders and Bas ter Weel, 2002; Oesch and Rodriguez Menés, 2010; Oesch, 2013). As argued by Hollanders and ter Weel (2002), the crude distinction between "unskilled" and "skilled" labor underestimates the variety of employment patterns related to skills.

literature has addressed the role played by technology in reshaping the quantity and quality of jobs. In terms of absolute change in jobs, the relationship between product and process innovation and employment has been analyzed at the firm, sectoral and country level (for reviews see Pianta, 2004; Vivarelli, 2015). In terms of the quality of jobs, different approaches have documented how innovation contributes to shape employment dynamics in terms of skills.

The Skill Biased Technological Change (SBTC) approach has pointed out the complementarity between new technologies and skills, predicting an increasing share of skilled workers (Autor et al., 1998; Chennels and Van Reenen, 1999; Acemoglu, 2002). More recently, the Routine Biased Technological Change (RBTC) approach has provided a novel technology-based explanation of employment changes focusing on tasks in terms of *routinization* of jobs (Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2014; Green, 2012; Ben-Ner and Urtasun, 2013). Besides technology, other factors explaining patterns of job polarization have included international trade and offshoring (Grosmann and Rossi-Hansberg, 2008; Blinder and Krueger, 2009; Mandelman, 2013; Oldenski, 2014), consumption spillovers (Manning, 2004; Mazzolari and Ragusa, 2012), ageing of population (Capatina, 2014).

Few studies, however, have taken into account the diversity of the directions technological change may take and the variety of innovative activities carried out in firms. In empirical studies, technology is usually proxied by R&D, patents or the adoption of ICTs as indicators which leave most innovative activities carried out in firms out of the analysis. The complex link between technologies and employment has been empirically detected by an increasing branch of literature (Bogliacino and Vivarelli, 2011; Pianta, 2001). However, few studies have interrelated the analysis of technologies with the skill dimension focusing on the impact that different technological strategies at sectoral level have on professional groups.

The dynamics of wages has also been investigated and again technology has emerged as a key factor in accounting for the effects of the increasing demand for high-skilled professionals in abstract tasks, and unskilled labourers in manual tasks (Hynninen et al., 2013). In a long term perspective, Brynjolfsson and McAfee (2014) have explored the complexity of digital technologies and their polarizing effects in terms of jobs, tasks and rewards.

A few studies have investigated the relationship between business cycles and employment polarization. Groshen and Potter (2003) have studied the 2001 recession in the US and its impact on job reallocation across industries. They argued that technological change, reorganization of production, local or international outsourcing have determined a permanent fall in demand that has resulted in permanent layoffs. The jobless nature of the recovery taking place since 2003 is therefore interpreted as the effect of the structural change in the US economy. In the same vein, Jaimovich and Siu (2012) investigated the 2008 crisis and found some effects on job polarization in the US; however, their analysis does not consider industry differences and structural change. Foote and Ryan (2012) explored employment polarization and its interaction with US business cycles using data on individual from the Current Population Survey. They assess the presence of synchronization in the employment dynamics over the business cycle of different skill groups and investigate the patterns of labor reallocation. Their results suggest that there is no evident relationship between employment polarization and business cycles, as all workers are likely to be equally affected by recessions and unemployed middle-skill workers rarely find new jobs during the upswings of the business cycle. A similar perspective has been adopted by Tuzemen and Willis (2013) who interpret job polarization as a long term structural phenomenon of the US economy, rather than the effect of business cycles. Focusing on middle-skill occupations, they detect an

acceleration of job losses during recessions – in particular in construction, manufacturing, education and health services - leading to an acceleration of polarization.
Finally, Faberman and Mazumder (2012) investigated the skill mismatch in the US labor market finding that it is more relevant for skilled workers rather than for middle skills and that there is no evidence of an acceleration of polarization during recessions.
The impact of the Great Recession on jobs in the US has been recently investigated by a set of studies edited by Card and Mas (2016), exploring the persistence of long term factors and the specificity emerged in the recent crisis. Kroft et al. (2016) have shown that the large job losses of 2009 have not been absorbed by new vacancies due to a slow demand dynamics. Moscarini and Postel-Vinay (2016) point out that – differently from past recoveries - small firms have failed to restart hiring in anticipation of large firms' behavior. The expanding trade with China – according to the results by Acemoglu et al. (2016) – has led to a 2% loss of US private sector employment between 1999 and 2011. Considering the skill structure of US jobs, Beaudry and Green (2016) identify since 2000 a contraction in the demand for skilled workers performing cognitive tasks that has led to a stagnation in their wages. Such trends – they argue – have been accelerated by the collapse of the US housing bubble. Therefore, high-skilled workers moved down the occupational ladder and displaced lower-educated workers in less skill-intensive jobs, suggesting a de-skilling pattern in the occupational structure. Moreover, the US recession appears to have reallocated production to more efficient firms to a lower extent than in past downturns, with modest effects on productivity improvements (Foster et al., 2016).
A comparison between such results for the US and European patterns is provided in this article.

3. The evolution of skills in Europe's industries

The dynamics of skills in European employment is investigated in this section with an analysis at the industry level, with consideration of four main professional groups that effectively account for the diversity of skills and for workers' positions in the production process.
An industry-level approach has two main advantages. First, it allows to relate skill dynamics to the evolution of technological activities, structural change and demand components for the whole economy. This avoids the limitations of most firm level studies which rely on panels that may not be representative of the universe of firms and whose results may fail to capture the business stealing effect where the job gains of innovative firms could be compensated by the losses of weaker firms in the same industry, resulting in no net employment growth (Bogliacino and Pianta, 2010). Moreover, as Sako (2008) pointed out, industry studies provide an institutional and historical context in which the dynamics of firms and workers can be investigated.
Second, an industry level analysis can use a wide range of indicators accounting for the complexity of technological activities, such as those provided by Europe's innovation surveys. Moving beyond the reliance on R&D and patents as proxies of innovation, the approach we adopt makes it possible to identify the main innovative strategies that emerge in industries, and in particular the relative importance of the development of new products and new processes.

Data and analysis

The empirical analysis is carried out on the Sectoral Innovation Database (SID) developed at the University of Urbino, containing industry-level information on 21 manufacturing sectors,

(from 15 to 37 Nace Rev.1), and 15 service sectors (from 50 to 74 Nace Rev.1)[2]. Countries included in the analysis are Germany, France, Italy, Spain and United Kingdom (GER, FR, IT, SP, UK)[3].
The database includes a large number of variables on employment and skills, innovation and economic activities, derived from three major sources: the *Labor Force Survey* (from Eurostat), the *Community Innovation Survey* (CIS, from Eurostat) and the *OECD Structural Analysis* (STAN) database.
The definition of skills we adopt moves beyond the high/low skill dichotomy, reliance on educational levels alone, and types of task. We use data on occupations from *Labor Force Surveys* based on the ISCO88COM nomenclature, and we define four main professional groups: Managers, Clerks, Craft workers and Manual workers, described in table 1 below. In our view the ISCO classification provides the most adequate representation of skills as it considers a wide range of information on workers' activities, including the typology of work, the level of autonomy in the workplace, the average education required, the position in firms' hierarchy, and labor compensation. Our definition of professional groups synthesize the multidimensional characteristics of jobs, ranking skill groups according to competences and wages (for a detailed analysis see Cirillo et al., 2014).

INSERT - Table 1

Data on technology is drawn from Europe's innovation surveys - CIS 2 (1994-1996), CIS 3 (1998-2000), CIS 4 (2002-2004) and CIS6 (2008-2010) – and include information on the shares of firms in each industry performing some kind of innovation (only product, only process, both product and process) and on the expenditure per employee devoted to R&D and to innovation-related machinery. Finally, industry-level data on wages and economic performance are drawn from the OECD STAN database[4].

A preliminary investigation of the dynamics of skills in Europe is carried out in this section exploring three main issues: a) the long term evolution of each professional group; b) the general relationships between technology and different skills; c) the importance of business cycles.

The dynamics of skills

The long term evolution of employment in professional groups is investigated with reference to the 1999-2011 period, an adequate time span for identifying structural changes and avoid temporary turbulence in job dynamics. In the econometric analysis of section 3 below percentage changes in employment over this period are related to technology variables

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[2] See Pianta et al. (2015) for a detailed description of the database. Due to the change in the classification system of industries after 2008, we transform employment data of the latest years expressed in Nace Rev.2 classes into the older ones (Nace Rev.1) applying the conversion matrix developed in Perani and Cirillo (2015), so that we can investigate a standardized data series for the entire time span 1999-2011.
[3] These countries account for a very large part of Europe's economy and, due to their larger size, assure the greatest available coverage of industries and data reliability for all the variables we use.
[4] As a wage variable, we use labor compensation per employee, which includes social contributions.

calculated as averages of the four CIS waves listed above and to educational shares for a central year, 2005.
Figure 1 shows – for the aggregate of the five EU countries - the changes in each professional group over the whole period we considered 1999-2011, with a break down for manufacturing and services. The evolution of skills in Europe combines *upskilling* – typical of manufacturing where employment falls - and *polarization* – typical of services, where most of the job growth takes place. In terms of shares of total employment, services have the highest concentration of managers and clerks, while in manufacturing craft and manual workers account for the largest share of jobs.

INSERT - Figure 1

In manufacturing, managers are the only professional group growing, while major job losses are concentrated in all other groups. Services did create new jobs – a 2.11% increase between 1999 and 2011 - mainly for managers, with increases for clerks and manual workers too. In all cases, craft workers have a worse dynamics than manual workers, reflecting the expansion of ancillary jobs in low qualified activities (Eurofound, 2013) that is a key element of the pattern of polarization.
Behind this overall picture for the aggregate of five EU countries, national patterns are very different, combining in different ways upskilling, polarisation and the shift from manufacturing to services. Growth in managers is stronger in Spain, Italy and France - where catching up effects in the skill structure could be relevant – and increases in manual workers are found in Germany, Spain and Italy. Conversely, job losses in craft workers are particularly strong in France and the UK.
The combination of changes within industries and of structural shifts between manufacturing and services is investigated with a shift-share analysis (see Table A1 in the Appendix).[5]. The expansion of services appears to be the main driver of managers growth, while manufacturing downsizing is associated to the fall of craft and manual workers. Within industries, *upskilling* emerges as a dominant trend in manufacturing while in services polarization prevails. From this empirical overview, a rather complex picture of structural change, upskilling and polarization emerges.

Technologies and skills

The skill bias effect of technological change has been widely investigated. A simple empirical evidence is provided in Figures 2 and 3, where the share of firms introducing innovations (either new products or new processes) is plotted against the shares of managers and manual workers in total employment. The contrasting effects of innovation are evident; in Figure 2 a broad positive association emerges, with more innovative industries showing higher shares of Managers, Professionals and Technicians, although with a wide dispersion due to industry and country diversity. In Figure 3 the negative relationship between innovation and shares of manual workers emerges, as new processes have the main aim of replacing low skilled workers and new products are associated to higher skill intensity of jobs. Behind this overall pattern, the specific impact of different innovation strategies – based on a more detailed set of indicators – is investigated in the next section.

[5] Percentages have been calculated applying the decomposition algorithm used by Berman et al. (1998) described in the Appendix. See Cirillo et al. (2014) for a detailed empirical analysis of patterns of change.

INSERT - Figure 2

INSERT - Figure 3

Skills and Cycles

The patterns documented above are strongly affected by business cycles. In this analysis we consider the 2002-2007 upswing and the 2007-2011 downswing. Figure 4 shows total employment changes in each professional group in the two periods for the aggregate of five EU countries.

Figure 4 highlights important characteristics of the skill dynamics. First, the 2002-2007 expansion appears to be largely a jobless recovery in Europe too; employment growth over this period is a meager 0.67% per year. Conversely, the 2007-2011 recession has led to major job destruction, with a 2.48% employment fall per year. Second, the upswing is dominated by skill polarization, with a large expansion of managers and a modest growth of manual workers, with limited losses in mid-skill occupations. Conversely, the downswing is characterized by a structural shift in the skill structure where losses are concentrated in craft and manual workers; behind the resulting apparent upskilling there is a combination of structural change from declining, blue-collar dominated manufacturing to services, and the "survival" in their jobs of more skilled employees.

This picture is confirmed when we separately analyze manufacturing and services; however, considering their different long-term dynamics, manufacturing shows an employment contraction even in the upswing, while services keep creating jobs also in the downswing.

INSERT – Figure 4

4. The econometric estimation

The econometric specification we propose to study skill dynamics in Europe builds on existing literature and takes into account the findings of the descriptive analysis of the previous section, highlighting the complexity of the relationships at work. Much of the literature modelling changes in the employment or wage structure relies on a translog cost function (Berman et al., 1994; Hollanders and ter Weel, 2002; Machin and Van Reenen, 1998; Adams, 1999; Foster et al., 2013) developed from Christensen et al. (1973) where the employment shares of skills are investigated as a function of different factors. Considering the importance of the absolute employment changes documented above, we modify this approach considering rates of change rather than shares as dependent variables. The explanatory factors we consider include on the one hand the "micro" variables used in the literature – such as wages and education – and, on the other hand, we include different technology variables and indicators of demand accounting for the structural evolution of industries.

We build on previous work on the dynamics of aggregate employment carried out at the industry level and on models that include different technology variables, wages and demand factors (see Bogliacino and Pianta, 2010; Bogliacino et al., 2013; Bogliacino and Vivarelli, 2011). In particular, we use variables that are able to account for the diversity of innovation strategies aiming at improving either technological competitiveness – through R&D or overall innovation - or cost competitiveness – through expenditure for new machinery or

adoption of innovation from suppliers. Previous studies have shown that at the industry level the employment impact of the former is generally positive, while the latter tends to have job destruction effects (Pianta, 2004, Vivarelli, 2015).
In the model we also include aggregate industry demand as a factor shaping growth opportunities. In several studies on the employment impact of technology, demand – proxied by value added and by its components - has emerged as a key driver (see Vivarelli, 1995; Crespi and Pianta, 2008; Guarascio et al., 2014); in particular, an expanding demand at the industry level is a necessary condition for allowing the job creation effects of product innovation to emerge.
Finally, wages are expected to have an inverse relationship with employment creation, as in standard labor market models; this relationship, however, is likely to vary across the professional groups we investigate.
The econometric specification applied to study the determinants of employment growth derives from a translog model where as in Adams (1999) capital and technology stocks are assumed to be quasi-fixed. Wages, education, technologies and aggregate demand are considered as the main drivers of employment change. Our estimates on the aggregate employment change are based on the following labour equation:

$$\Delta emp_{it} = \beta_5 \Delta VA_{it} - \beta_1 \Delta w_{it} + \beta_2 edu_{it} + \beta_3 \Delta tc_{it} - \beta_4 \Delta cc_{it} + \varepsilon_{it} \qquad (1)$$

where Δemp is the compound annual rate of change of employment, Δw is the compound annual rate of change of labor compensation (changes in labor costs), edu is the share of workers with higher education, tc and cc are proxies for the *technological* and the *cost competitiveness* strategies, VA is value added, a proxy for demand, and ε is the error term, for industry i and time t. The model is estimated at industry level for five European countries, the individual observation is a certain industry in a given country at a certain time. We introduce specific country effects in order to account for differences in country characteristics and sector specificities. Accounting for national patterns is important in terms of national system of industrial relations and welfare institutions, as well as economic and employment structures.

As a baseline equation, we estimate the following labor demand curve that can be assumed to be the result of a cost minimisation programme by a firm with a translog cost function:

$$y_{it} = x'_{it}\beta + u_i + v_{it} \quad (2)$$

where y_{it} is the employment variable, x_{it} the vector of regressors, u_i the individual/sectoral effect and v_{it} the random disturbance, for industry i and time t. Equation 2 can be assumed to be the result of a cost minimisation programme by a firm with a translog cost function. If variables are expressed in log scale, we can eliminate the individual effect by taking the first difference of equation (2).

$$y_{i,t} - y_{i,t-1} = \beta(X_{i,t} - X_{i,t-1}) + (u_i - u_i) + (v_{i,t} - v_{i,t-1})$$
$$\Delta y_{i,t} = \beta \Delta X_{i,t} + \Delta v_{i,t} \qquad (3)$$

In this way, the sectoral unobserved component u_i potentially leading to biased estimates due to its correlation with the error component $v_{i,t}$ is differentiated out. This transformation permits to apply Ordinary Least Squares Estimator (OLS).
As known, the difference in log approximates the rate of change, thus we express both dependent variable and regressors in rate of variation. Instead of considering long differences,

we compute the compound annual growth rate. Innovation variables are not expressed in rates but as either shares of firms in the sector or expenditure per employee. This can be justified considering innovative efforts intrinsically dynamic and deemed to capture the change in the technological opportunity set available to the industry (Bogliacino and Pianta, 2010).
Taking differences of variables, the model can be estimated consistently using OLS. Furthermore, the model is adjusted for heteroscedasticity (robust standard errors) and intra-group correlation at the industry level, checking for intra-sectoral heterogeneity. Dealing with different sized groups, heteroscedasticity is quite common. We use a Weighted Least Squares procedure using the average number of employees over the period 1999-2011 as a weight. We also control for the possibility of multicollinearity between regressors through a VIF (Variance Inflation Factors) test.
Model (1) is first estimated on changes in total employment in order to account for overall job dynamics. We then estimate the same model for each professional group in order to explore regularities and diversities in such relationships. We estimate a system of labor demand equations for managers, clerks, craft and manual workers - as in Hijzen et al. (2005) and Foster et al. (2012) - using seemingly unrelated regressions (SUR, Zellner, 1962). Such method allows that changes in one skill group may affect changes in the other ones. The model estimated for the four professional groups is expressed in equation (4):

$$\begin{gathered}\Delta managers_{it} = \beta_1 \Delta VA_{it} - \beta_2 \Delta w_{it} + \beta_3 edu_{it} + \beta_4 \Delta tc_{it} - \beta_5 \Delta cc_{it} + \varepsilon_{it} \quad (4)\\ \Delta clerks_{it} = \beta_1 \Delta VA_{it} - \beta_2 \Delta w_{it} + \beta_3 edu_{it} + \beta_4 \Delta tc_{it} - \beta_5 \Delta cc_{it} + \varepsilon_{it}\\ \Delta craft\ workers_{it} = \beta_1 \Delta VA_{it} - \beta_2 \Delta w_{it} + \beta_3 edu_{it} + \beta_4 \Delta tc_{it} - \beta_5 \Delta cc_{it} + \varepsilon_{it}\\ \Delta manual\ workers_{it} = \beta_1 \Delta VA_{it} - \beta_2 \Delta w_{it} + \beta_3 edu_{it} + \beta_4 \Delta tc_{it} - \beta_5 \Delta cc_{it} + \varepsilon_{it}\end{gathered}$$

We control for endogeneity testing whether our proxy for demand in the model is effectively exogenous in determining the change in employment by skill. As a further control, we instrumented value added through profits, lagged profits and innovation. Conversely, we assume that in European industries wage changes do not react in the short term to changes in employment as industries are characterized by different institutional arrangements, collective contracts and bargaining processes, thus allowing an exogenous treatment of wages. Results are shown in the next section.

5. Results

Table 2 reports the OLS estimation for total employment and the result of the seemingly unrelated regressions for the four professional groups.[6] Results confirm expected relationships and identify significant differences for skill groups.
Changes in total employment are affected by demand growth – proxied by value added – and negatively related to wage increases; higher shares of workers with tertiary education are associated to job growth. The contrasting effects of innovation are documented by the share of innovating firms - a proxy for the search for technological competitiveness – showing a positive employment impact, and by the share of firms having suppliers as sources of

[6] All coefficients are corrected for heteroscedasticity. For the Seemingly unrelated regressions we have calculated the Breusch-Pagan test of independence on the correlation matrix of residuals; the result allows to reject the hypothesis of independence between residuals for the four professional groups ($\chi^2_{(6)} = 51.876$). The seemingly unrelated regression model is therefore consistent and efficient.

innovation - a proxy for cost competitiveness - which has a negative impact on jobs; both coefficient have the same magnitude.[7]

In the regression we include country dummies and dummies for the four Pavitt classes (Science Based, Specialized Suppliers, Scale Intensive and Suppliers Dominated), in order to account for sectoral heterogeneity[8].

Results for the professional groups show commonalities and differences with the benchmark provided by the findings for total employment. Demand changes affect all professional groups but have stronger effects on craft and manual workers. Wage increases negatively affect all professional groups but have stronger effects on mid-skills – clerks and craft workers. In such professional groups the elasticity of employment to demand and wages appears to be higher, with a performance that is closer to the standard operation of labor markets.

INSERT - Table 2

Surprisingly, while the share of workers with tertiary education was relevant for explaining total employment, this variable loses its significance for managers; we replace it with the share of workers with secondary education in the other three professional groups and it emerges as significant and negative for craft workers alone. At the level of skill groups it is likely that the information available on educational levels are inadequate to account for the type of knowledge relevant for such jobs, and the positive impact of education could be captured by the variable on industry innovativeness.

Considering now the contrasting effects of technology, we find that the positive effect of high shares of innovating firms and the negative effect of reliance on suppliers (the proxy for process-oriented innovation) are significant for managers only. For clerks job losses are associated to higher share of innovating firms (while suppliers lose significance), suggesting that technological change as a whole has an employment reduction effect.

Also for craft and manual workers the potential job-creating effect of new products does not emerge; when industries succeed in bringing new products to markets, the jobs that are created are only at the top of the skill hierarchy. We have seen in the descriptive analysis that managers is the only skill group with a strong expansion of employment; these results suggest that innovation supports such expansion, while the potential benefits of technology are lost for the other professional groups.[9] The only significant effect of technology on lower skills comes from the negative coefficient of the importance of suppliers in the manual workers equation; again, the negative effects of (process) technology emerge as the dominant one for the lower skilled.

Controls for country and Pavitt classes are included in these regressions; broadly similar results have been obtained with separate estimates for manufacturing and services (Cirillo, Pianta, Nascia, 2014).

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[7] The results on the contrasting effects of different types of innovation confirm previous findings at the industry level (Bogliacino and Pianta, 2010; Bogliacino et al. (2013). They are also consistent with the micro-econometric evidence from firm-level data obtained from the third wave of the Community Innovation Survey for France, Germany, Spain, and the UK (Vivarelli, 2014).

[8] See the Appendix for the list of industries in Pavitt classes.

[9] A large literature has shown that lower skills are more easily offshored even when industries expand and new products are introduced; a preliminary analysis of the impact of offshoring and technology on professional groups is consistent with our results (Bramucci, 2015).

The robustness of this specification has been tested in a number of ways. First, in order to test the exogeneity of value added we have instrumented it through the growth of profits (operating surplus) that is correlated with the rate of change of value added, but is determined by the distributive dynamics. We carry out a Two Stages Least Squares regression and we find that our results are broadly confirmed. In Table A2 in the Appendix we report the findings. The main differences from those of Table 2 above include a lower significance of the value added for the professional groups; the positive and significant effect of tertiary education on employment growth of managers; the emergence of a positive impact of innovative activities for craft and manual workers, showing again the contrasting effects of technology. In addition, we also carried out estimations where value added is instrumented with the logs of 1995 profits (in order to allow for lagged effects), again obtaining similar results and we have tested for the possibility of reverse causality (see the Appendix).

The estimation for business cycles

We now turn to the investigation of how the relationships so far identified are affected by business cycles. As already pointed out, we consider the 2002-2007 upswing and the 2007-2011 downswing separately. First we test the structural stability of the time series of total employment estimated in table 3 below comparing a single period with the break of series in 2007; the Chow test shows the presence of a structural break.[10]

We estimate the same model of equation (1) for total employment and for each professional group with an interaction between each regressor and the time period identifying the upswing and the downswing; the econometric methodology is the same one adopted for the estimation of total employment in Table 2 above. We then compare the resulting coefficients in order to understand how the business cycle affects the relationships documented above, following the approach proposed in Lucchese and Pianta (2012).

Table 3 shows the results. Total employment is again affected by changes in demand with no difference between expansion and recession. Wage increases negatively affect job changes in the upswing only; during the recession, job losses across industries were not associated to the importance of wage dynamics. The share of workers with tertiary education is also significant in the recovery alone. As technology indicators we use here R&D expenditure per employee – as a proxy for technological competitiveness – and expenditure for new machinery - as a proxy for cost competitiveness. The former has a positive and significant effect on job changes in the expansion only; the latter has a negative effect in both periods. The contrasting effects of different technology strategies again clearly emerge. Country dummies and a dummy for manufacturing sectors have been included in this estimation.

INSERT - Table 3

How do the four professional groups perform compared to this benchmark? Change in value added is relevant for job changes in all four professional groups during the upswing; the

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[10] Under the null of equal coefficients and no structural break, we reject H_0 with $F_{11,289}=5.25$ and a critical value of 1.75 at 5% of significance level. For this analysis we calculate average annual rates of change of employment and wages for the two periods; technology variables are computed as averages of CIS 2 and 3 for the first period, and CIS 4 and 6 for the second one. Educational shares are calculated for 2002 for the first period and 2005 for the second one.

highest coefficients are for craft and manual workers. During recession, this relationship holds for clerks only.
Increases in labor compensation show a negative effect on job changes in all groups except manual workers – where wages tend to be so low that may not significantly affect labor demand. The wage elasticity of employment is highest for craft workers. During the recession again labor compensation loses its impact on job changes across industries. Education variables are not included in this estimation as they are the least affected by cyclical patterns.
The impact of technologies on professional groups again confirms its dual nature. The employment of managers is the only one that captures the benefits of new products during the upswing and is not significant during the downswing. Clerical jobs are lost during recession as a result of higher R&D expenditures. Craft and manual workers do not appear to be affected by new products neither in the upswing nor in the downswing. The expenditure on new machinery which proxies process innovation has a strong and generalized negative impact on employment. During the expansion managers and clerks experience the negative effects of new process; during the recession all professional groups suffer job losses as a consequence of new processes, with craft and manual workers being hit hardest. Again, country dummies and a dummy for manufacturing sectors have been included in this estimation.
The picture emerging from these results shows that in the recession started in 2007 most relationships driving the evolution of skills in Europe have broken down. While total employment has followed the collapse of demand and value added, job losses in professional groups have not been associated the dynamics of either value added or wages, suggesting that industries and skills have been hit by the crisis in a differentiated way. The impact of technology adds a new depth to the evidence provided above. The potential that product innovations have for expanding total employment can be found during the upswing alone. But managers are the only professional group that accounts for such job expansion, and the benefits of technology are in fact not available for less skilled workers. During the recession the introduction of new products slows down and their positive employment effect is lost for all workers. In the downswing industries tend to concentrate on restructuring and the introduction of new processes, with generalized employment losses in all skill groups except managers; for craft and manual workers the negative effects are particularly heavy in manufacturing. These results confirm the findings of Lucchese and Pianta (2012) on the impacts on total employment of new products and processes over the cycle, and provide original evidence on how each professional group is affected by the combination of technological change and business cycles.

6. Conclusions

In this article we have shed new light on the dynamics of skills with improvements in our understanding of the diversity of professional groups, of the role of technology and of the impact of business cycles.
First, we have shown that the skill dimension of jobs is crucial to understand changes in employment. Our ISCO-based definition of four professional groups – reflecting a multidimensional view of employment qualification – effectively captures differences in job dynamics. The descriptive analysis has documented the combination of upskilling and polarization that is taking place in Europe’s manufacturing and service industries. Our econometric analysis on the determinants of employment change has shown that each professional group is characterized by a specific set of effects of technological activities, demand and wages, which qualify the benchmark resulting from the determinants of total employment.

Second, the conceptualization of technology as a complex phenomenon has allowed us to distinguish between the dominance of product-oriented efforts to improve technological competitiveness, and a strategy relying on labor-saving technologies. At the industry level, the former has emerged as having a positive impact on total employment, while the latter has a job reduction effect; this confirms the findings of a large literature (surveyed in Pianta, 2004; Vivarelli, 2015). In this article we show that these contrasting effects are unevenly distributed across skill groups; managers concentrate the job-creating effects of new products while craft and manual workers suffer most the negative impact on new processes.

Third, we have shown that such relationships are not independent from business cycles. The long run effects of technological change on jobs and skills – alongside the impact of demand and wages – have been disrupted in the recession started in 2007. For total employment, the positive impact of new products on job growth is confirmed during the upswing, but disappeared in the recession. Conversely, in the downswing large job losses associated to industry restructuring and new processes emerge. When we break down employment by professional groups major novelties become visible. The gains in the expansion are concentrated in managers, while in the recession the largest losses hit craft and manual workers.

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Appendix

The decomposition of employment change by skills

In order to provide a precise picture of employment change by skills within and between industries, we apply the decomposition procedure proposed by Berman et al. (1998):

$$\Delta s = \sum_i \Delta e_i \, \overline{s_i} + \sum_i \overline{e_i} \, \Delta s_i$$

where s is the share of a skill group in the economy, $\overline{s_i}$ is the average share over the period, e is the share of total employees in an industry in relation to total employment, $\overline{e_i}$ is the average share of employees over the period, i is the sector. Results are in Table A1 below.

Table A1. Decomposition of employment change (1999-2011)

	MANAGERS		CLERKS		CRAFT W.		MANUAL W.	
Sectors	Between industry	Within industry	Between industry	Within industry	Between industry	Within industry	Between industry	Within industry
MANUFACTURING	-2.47%	3.67%	-1.03%	0.11%	-2.32%	-1.60%	-2.63%	-2.19%
SERVICES	3.27%	1.70%	3.01%	-1.78%	0.38%	-0.64%	1.78%	0.72%
TOTAL CHANGE	0.80%	5.38%	1.98%	-1.67%	-1.94%	-2.24%	-0.85%	-1.47%

Table A2. Determinants of employment growth in professional groups in European industries, 1999-2011. Instrumental Variable Approach (bootstrapped standard errors)
Rate of growth of value added instrumented with the rate of growth of operating surplus.

Dependent variable:	Tot Employment	Managers	Clerks	Craft Workers	Manual Workers
Value Added (rate of growth) instrumented	0.3771	0.1681	0.2756	1.0158	0.4355
	(0.1456)***	(0.2292)	(0.2301)	(0.3950)**	(0.2839)
Labor compensation per employee (rate of growth)	-0.4900	-0.4460	-0.4932	-0.4348	-0.5206
	(0.0790)***	(0.1267)***	(0.1196)***	(0.2505)*	(0.1252)***
Share of Tertiary Education	0.0531	0.0461			
	(0.0199)***	(0.0220)**			
Share of Secondary Education			-0.0080	-0.0414	0.0561
			(0.0282)	(0.0770)	(0.0370)
Share of firms performing innovation	0.0652	0.0889	0.0723	0.1512	0.1494
	(0.0245)***	(0.0434)***	(0.0445)	(0.0763)**	(0.0691)*
Share of firms having suppliers as sources of innovation	-0.0648	-0.1250	-0.0674	-0.0076	-0.0863
	(0.0240)***	(0.0579)**	(0.0391)*	(0.0911)	(0.0468)*

Pavitt dummies (SB-SS-SI-SD)	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
	0.7082	0.6902	0.5555	0.4065	0.5551
N observations	183	183	181	165	174

A test on reverse causality

Due to the inefficiency of the conventional Instrumental Variable regression in the presence of heteroscedasticity, we apply as estimator the generalized method of moments (GMM), introduced by Hansen (1982).
After estimating the model with instrumented value added through GMM estimator, we perform the Hayashi (2000) C statistic, also known as the difference-in-Sargan statistic and we do not reject the null of exogenous regressors [$\chi^2_{(1)}$=0.1622]. Then, we can conclude that OLS estimations are correct due to the exogeneity of the change in value added in the specification that we have adopted.

A further control we have carried out concerns the possibility of a reverse causality between employment – namely in high skills – and value added, a problem that is typical of firm level studies. New growth theories assume that higher skills can be a determinant of economic performance and several studies have explored such complex relationships (Guellec and Van Pottelsberghe de la Potterie, 2004; Ulku, 2007). In order to exclude the presence of reverse causality, we have applied the Hausman procedure consisting in saving the residuals from the structural model and including them in the final model. We first estimate the baseline model of table 2 using change in Value Added for the period 1999-2011 as dependent variable and omitting the change in employment as regressor (equation 5). We save the residuals of this first stage and we perform a second estimation as the one in equation (1) adding also the residuals saved from equation (5).

$$\Delta VA_{i,t} = -\beta_3 \Delta w_{i,t} + \beta_4 edu_i + \beta_1 \Delta tc_{i,t} - \beta_2 \Delta cc_{i,t} + \Delta \varepsilon_{i,t} \quad (5)$$

We obtain an F statistic ($F_{1,164}$=1.79) that supports our approach; we cannot reject the null of exogeneity of the change in Value Added in the employment regression estimation. Therefore we can rely on model (1) for estimating employment changes.

The Revised Pavitt taxonomy for manufacturing and service industries

Bogliacino and Pianta (2013) proposed the Revised Pavitt taxonomy for manufacturing and service that is used in this paper. The groups of industries are the following:

SCIENCE-BASED: Chemicals; Office machinery; Manufacture of radio, television and communication equipment and apparatus; Manufacture of medical, precision and optical instruments, watches and clocks; Communications; Computer and related activities; Research and development.

SPECIALISED SUPPLIERS: Mechanical engineering; Manufacture of electrical machinery and apparatus n.e.c.; Manufacture of other transport equipment; Real estate activities; Renting of machinery and equipment; Other business activities.

SCALE INTENSIVE: Pulp, paper & paper products; Printing & publishing; Mineral oil refining, coke & nuclear fuel; Rubber & plastics; Non-metallic mineral products; Basic metals; Motor vehicles; Financial intermediation, except insurance and pension funding; Insurance and pension funding, except compulsory social security; Activities auxiliary to financial intermediation.

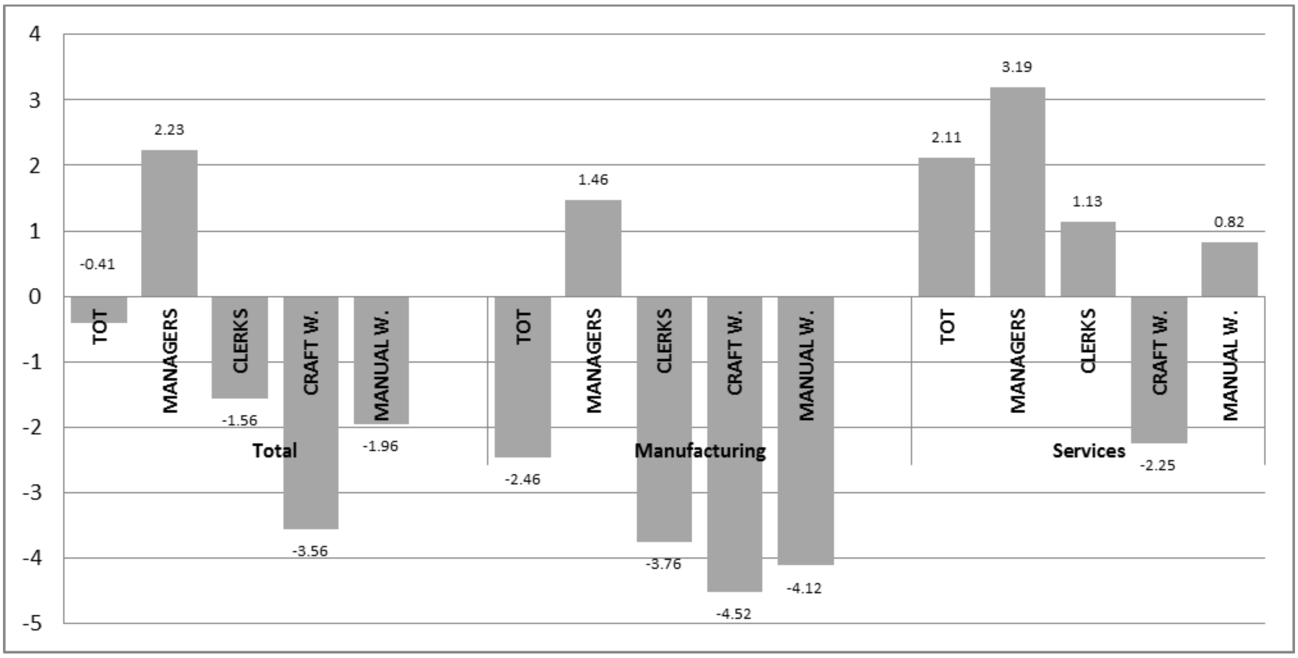
SUPPLIER DOMINATED: Food, drink & tobacco; Textiles, Clothing, Leather and footwear; Wood & products of wood and cork; Fabricated metal products; Furniture, miscellaneous manufacturing, recycling; Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel; Wholesale trade and commission trade, except of motor vehicles and motorcycles; Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods; Hotels & catering; Inland transport;Water transport; Air transport; Supporting and auxiliary transport activities; activities of travel agencies.

Table 1. The professional groups

Professional groups	**ISCO 1 digit classes**
Managers	Managers, senior officials and legislators
	Professionals
	Technicians and associate professionals
Clerks	Clerks
	Service and sales workers
Craft workers	Skilled agricultural and fishery workers
	Craft and related trade workers
Manual workers	Plant and machine operators and assemblers
	Elementary occupations

Figure 1. Rate of change of employment by professional groups, 1999-2011

Average annual rates of change, manufacturing and services, five major EU countries



Source: LFS, own elaboration.

Figure 2. Innovative firms and shares of managers in employment

Averages 1999-2011, five European countries, 38 manufacturing and service industries, percentages

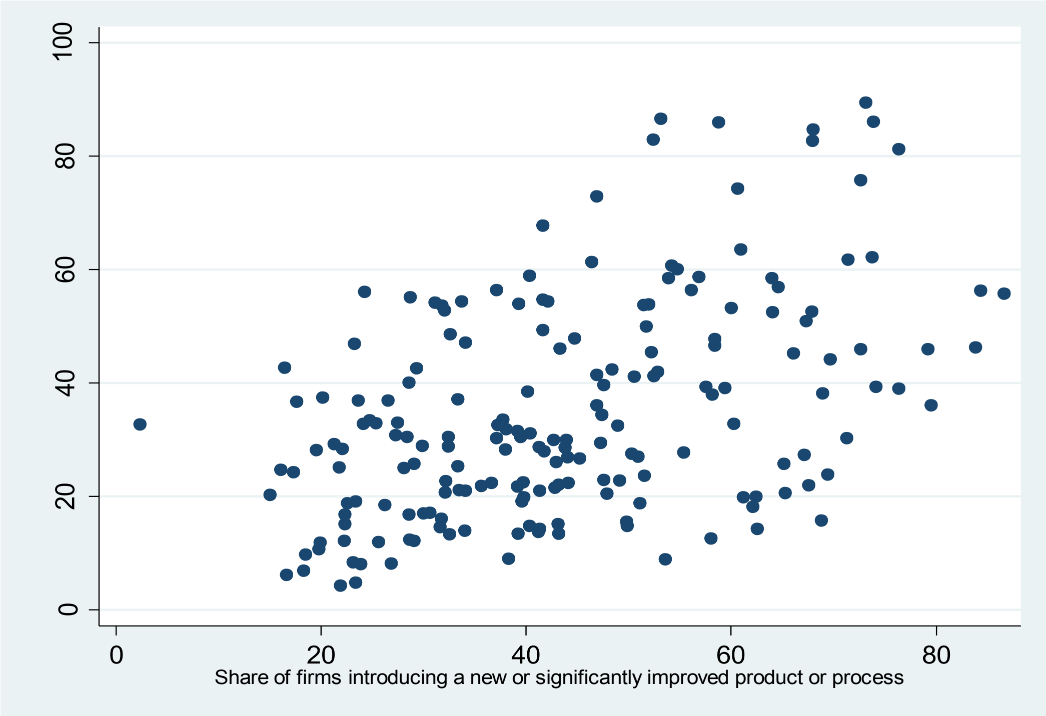


Figure 3. Innovative firms and shares of manual workers in employment

Averages 1999-2011, five European countries, 38 manufacturing and service industries, percentages

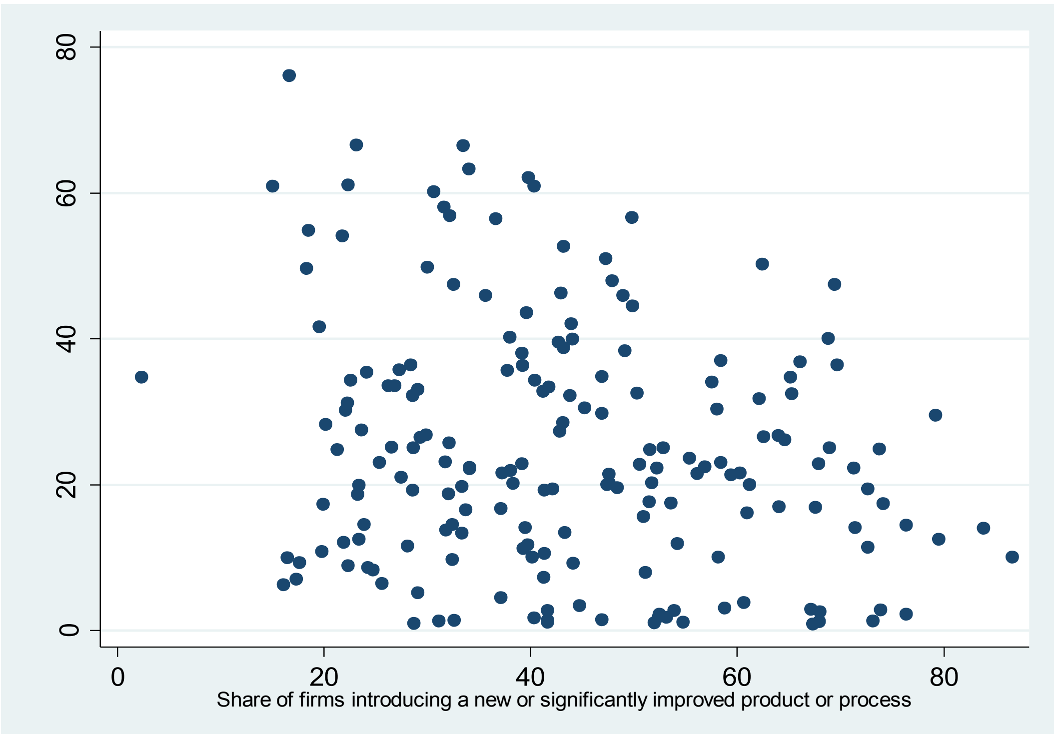
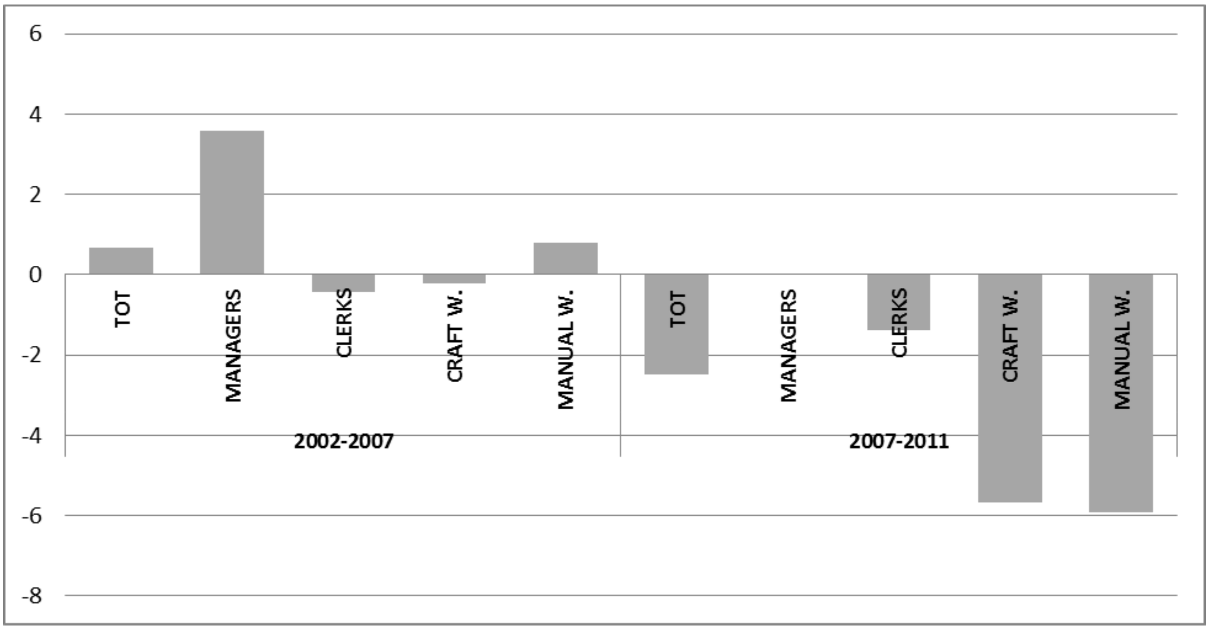


Fig. 4 Average growth rates, 2002-2007 (upswing) and 2007-2011 (downswing)
Average annual rates of change of total employment in manufacturing and services, five major EU countries



Source: LFS, own elaboration

Table 2. Determinants of employment growth in professional groups in European industries, 1999-2011.
OLS estimation of Total employment; Seemingly unrelated regressions for Professional groups.

Dependent variable:	Total Employment	Managers	Clerks	Craft Workers	Manual Workers
Value Added (rate of growth)	0.4635	0.4753	0.473	0.5565	0.616
	(0.0785)***	(0.0872)***	(0.1434)***	(0.1995)***	(0.1430)***
Labor compensation per employee (rate of growth)	-0.5036	-0.5783	-0.7788	-0.6598	-0.4916
	(0.0632)***	(0.0738)***	(0.1208)***	(0.1691)***	(0.1209)***
Share of Tertiary Education	0.0522	0.0078			
	(0.0185)**	(0.0199)			
Share of Secondary Education			0.0016	-0.0849	0.027
			(0.0291)	(0.0333)**	(0.0265)
Share of firms performing innovation	0.0642	0.0727	-0.0927	0.1028	0.0411
	(0.0220)**	(0.0298)**	(0.0474)**	(0.0663)	(0.0481)
Share of firms having suppliers as sources of innovation	-0.0663	-0.1606	-0.0151	-0.0139	-0.1194
	(0.0193)***	(0.0348)***	(0.0566)	(0.0794)	(0.0577)**
Pavitt dummies (SB-SS-SI-SD)	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.786	0.6024	0.5054	0.4553	0.5302
N observations	181	161	161	161	161

Robust Standard Errors in parentheses:
* significant at 10%, ** significant at 5%, *** significant at 1% level

Table 3. Determinants of employment growth in professional groups in European industries, in upswings (2002-2007) and downswings (2007-2011).

Dependent variable:	Total Employment	Managers	Clerks	Craft Workers	Manual Workers
Value Added (rate of growth) (UP)	0.2773	0.3613	0.2460	0.6339	0.4246
	(0.0858)***	(0.1214)**	(0.1409)*	(0.2469)**	(0.2175)*
Value Added (rate of growth) (DOWN)	0.2707	0.2132	0.4244	-0.2187	0.2220
	(0.0933)**	(0.1629)	(0.2077)***	(0.5042)	(0.2866)
Labor compensation per employee (rate of growth) (UP)	-0.2242	-0.2952	-0.1497	-0.5248	-0.1216
	(0.0464)***	(0.0724)***	(0.0687)**	(0.1834)**	(0.0924)
Labor compensation per employee (rate of growth) (DOWN)	-0.0127	-0.0370	-0.0069	0.2727	0.0657
	(0.0394)	(0.0639)	(0.0747)	(0.2170)	(0.1040)
Share of Tertiary Education (UP)	0.0717				
	(0.0238)**				
Share of Tertiary Education (DOWN)	0.0276				
	(0.0242)				
Expenditure in R&D per employee (UP)	0.1595	0.2384	-0.0766	0.1256	0.0959
	(0.0949)*	(0.1429)*	(0.1067)	(0.2601)	(0.1684)
Expenditure in R&D per employee (DOWN)	0.0732	-0.0340	-0.2830	0.3106	0.4254
	(0.0905)	(0.1479)	(0.1634)*	(0.4079)	(0.3731)
Expenditure in Machinery per employee (UP)	-0.4109	-0.7135	-0.1219	-0.3806	0.5326
	(0.2309)*	(0.3867)*	(0.0386)**	(0.6677)	(0.4548)
Expenditure in Machinery per employee (DOWN)	-0.6533	-0.7998	-0.1483	-1.6568	-1.7156
	(0.2535)**	(0.3815)**	(0.0813)*	(0.9881)*	(0.5875)**
Country dummies	Yes	Yes	Yes	Yes	Yes
Manufacturing	Yes	Yes	Yes	Yes	Yes
R^2	0.4021	0.288	0.1581	0.1466	0.2275
N observations	311	311	312	297	302

Robust Standard Errors in parentheses:
* significant at 10%, ** significant at 5%, *** significant at 1% level