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OFFSHORING, EMPLOYMENT AND WAGES

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Abstract

This paper reviews the debate on the economic effect of the international fragmentation of production also known as "offshoring" and provides a preliminary investigation on the impact of imports of intermediate products on labor demand and wages in five European countries (Germany, Spain, France, Italy, United Kingdom). Data are obtained from the Sectoral Innovation Database (SID) of the University of Urbino, a large database that merges statistical material from various sources (LFS; CIS; OECD STAN; WIOD). The first part of this work is devoted to a discussion of the concepts, the economic effects of offshoring and the debate that followed. The second section presents offshoring trends and discusses the results of a preliminary econometric analysis on the offshoring effect on wages and employment. Results suggest that offshoring has a general negative impact on labour demand and wages although at a more careful examination high-tech offshoring appear to have a positive influence on wages of medium and high-skilled workers.

Keywords: *Offshoring, International Outsourcing, Innovation, Employment, Wages*

JEL classification: F1 F2

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1. Introduction

Over the last decades, globalization has led to a massive reorganization of production activities on an international scale, in a rapidly changing political and technological context. Phenomena such offshoring and international outsourcing - the relocation of production processes abroad, either to a foreign affiliate or to an external supplier - have dramatically increased. Thanks to a consistent drop in transportation and communication costs and to better communication technologies, firms are now able to organize their production system on global scale. Firms can profit from relocating production to developing and transition countries where labor costs are much lower than in the country of origin. In industrialized countries such as the US and Europe, this has led to the fear of deindustrialization but also to the fear of a “race to bottom” concerning home wages and working conditions. Fears surrounding offshoring have spurred a long-lasting debate that involved companies, consulting agencies, trade unions, politicians and economists.

The empirical literature dealing with the domestic effect of offshoring on home activities in developed economies is extensive and controversial. Indeed, thanks to production offshoring firms can improve domestic productivity and raise wages in home plants. Firms can also increase domestic operations and employment when offshore activities help to raise firms competitiveness and in turn to boost profits. However, while the economic benefits of offshoring may be to the advantage of some, others may suffer from its negative consequences in terms of lower employment levels and lower wages. Offshore operations require additional activities of supervision and coordination that are most likely located in the country of origin. Moreover, firms may very well expand domestic core activities such as marketing, design, R&D and highly specialized functions that require highly skilled personnel such as managers, supervisors and engineers. On the contrary, the activities that are relocated abroad are highly routinized tasks with a very low content of value added, and can be easily replaced by a low-qualified and low-paid workforce in less advanced economies.

Aim of this paper is to explore the impact of offshoring on employment and wages for different group of workers. A model that relates changes in employment and wages with offshoring, technology and demand variables is developed and empirically tested on a small group of five major EU countries (Germany, Spain, France, Italy and the United Kingdom). The novelty of the approach proposed with this model resides in the fact that employment is divided into four occupational groups, namely managers, clerks, craft and manual workers. While there are many studies that relate offshoring with the relative labor demand of white-collar and blue-collar workers, or high-skilled and low-skilled workers, there are no empirical studies that proposed a much more detailed differentiation of employment groups. The model proposed here uses industry-level data collected from various statistical sources and matched after a careful elaboration of the original material.

The paper is structure as follows. Section two will discuss the economics effects on offshoring on the domestic labor market presenting a short review of the empirical literature. Section three will present the data used for the empirical analysis as well as the econometrics methodology. Section four will conclude.

2. The Effects of Offshoring: a Review of the Literature

In industrialized countries, offshoring practices have become core ingredients of day to day business strategies. For this reason, there is great uncertainty around the potential consequences on domestic economic welfare. If on the one hand offshoring brings benefit to firms and consumers in terms of lower production costs and lower prices for final goods, on the other it may results in large employment losses and increasing wage differential. This is certainly the case of low-skilled workers that have now to compete with rapidly modernizing economies where low educated laborers are ready to be employed for a smaller fraction of their salary (OECD 2007). Despite the raging sentiment growing around these controversial investment practices the empirical literature dealing with the employment effects on offshoring has not yet come to a unified conclusion[1].

A first group of contributions evaluated the overall impact of offshoring on labor demand. In a set of widely cited papers, Amiti and Wei (2004; 2005) investigated the effect of service and material offshoring on employment in United Kingdom and US. The authors state that the fear of job loss in developed country such as US and UK is largely misplaced. Large industrialized countries such as US and UK tend to run surpluses in the trade flow of offshoring investment. This is particularly true for the computer and the ICT industry where the inflow of intermediate inputs largely offset the outflow of offshore investments.

Using data from 1995 to 2001 on 78 sectors (69 manufacturing industries and 9 service industries), Amiti and Wei (2004) find no evidence of service offshoring lowering the rate of job growth in United Kingdom. In the following contribution, Amiti and Wei (2005) used US manufacturing data from 1992 to 2000 to estimate productivity and employment effects of material and service offshoring. The authors found out that both material and service offshoring have positive effects on productivity accounting for, in the case of service offshoring, from 11 to 13 percent of productivity increase and from 3 to 6 percent increase in the case of material offshoring. Concerning employment, a small negative effect (less than one percentage point) is detected when industries are highly disaggregated (i.e. 450 industries). However, this effect seems to disappear when the analysis is performed at a more

[1] Due to the scope of this work, this section focuses on the results obtained from those studies that conducted empirical investigation with industry-level data although a number of other contributions have used firm and individual level data.

aggregate industry-level (i.e. 96 industries). According to the authors, this finding indicates that demand growth has offset the negative effect on employment exerted by offshoring.

Hijzen and Swaim (2008) use sectoral-level data from 1995 to 2000 for 17 OECD high income countries to evaluate the impact of both intra-industry and inter-industry offshoring on domestic employment. In line with the findings of Amiti and Wei (2004; 2005), the authors found out that offshoring has no negative effect or even a slightly positive effect on home industry employment. More specifically, while intra-industry offshoring reduce the labor intensity of production without affecting industry employment, inter-industry offshoring does not influence labor intensity but it rather positive influence the overall industry employment. To support their results, Hijzen and Swaim (2008) argue that productivity gains obtained through offshoring investment are able to completely offset jobs losses caused by offshoring.

OECD (2007) comes to a rather different conclusion. In this large and well-documented research, material and service offshoring appear to be detrimental to employment in home industries. The study uses a cross-sectional database for 12 OECD countries in the time range from 1995 to 2000 (including 26 manufacturing and service industries). The estimation follows the same econometric model proposed by Amiti and Wei (2004). Offshoring is measured with industry-level data obtained from standard I-O tables and is calculated as the proportion of imported intermediate inputs on total non-energy inputs. For all three model specifications investigated in the research, results show a negative sign for both foreign manufacturing and service offshoring coefficients.

More recently, Milberg and Winkler (2013) estimated the impact of offshoring on labor demand in the United States from 1998 to 2006. Contradicting previous expectations, regression results show that service and material offshoring lead to lower employment levels. The authors suggest that if previous results showing the positive effect of offshoring on employment are correct, three possible leakage effects have impede offshoring to positively influence labor demand: (i) foreign lower input prices do not reduce price of domestic output, (ii) lower output prices do not stimulate output demand and (iii) higher labor demand do not follow to higher output demand. Milberg and Winkler results are in contrast with the findings of Amiti and Wei (2005) that with the same dataset, although in a shorter time span, find no negative effect of service offshoring on employment.

The international fragmentation and relocation of production activities do not only affect total labor demand but also the relative composition of employment within industries. Offshoring can influence economic activity at home by changing the international division of labor, the skill intensity and the composition of the workforce. The transfer of labor-intensive tasks abroad requiring unskilled workers increases the level of high-skilled workers at home where high-skill intensive activities are concentrated. While this might improve the overall level of productivity and increase average wages at home, low-skilled workers will be penalized as less qualified and routine tasks are easier to offshore than high-skilled tasks.

For this reason, a number of empirical studies have investigated the impact of production offshoring on the change in the skill-composition of employment. Feenstra and Hanson (1996) paved the way in emphasizing the role material offshoring has in influencing labor demand dynamics. The authors computed broad material offshoring measures for 435 US industries from 1972 to 1992. The research found that offshoring is responsible for 31 to 51 percent increase in the wage bill of non-production workers used here as proxy for high-skilled laborers (Feenstra and Hanson 1996). In the following contribution (Feenstra and Hanson 1999), results shows that narrow material offshoring explains from 11 to 15 percent increase in the wage share of non-production (high-skilled) workers.

Very similar results are found for France. Strauss-Kahn (2003) found that in the period from 1977 to 1993 international outsourcing increased from 9 to 14 percent and that it substantially contributed to the decline in the share of less-skilled workers, in particular in the manufacturing industry. According to the research, in the period from 1977 to 1985, outsourcing was responsible for 11 to 15 percent of the decline in the share of unskilled workers. In the period from 1985 to 1993, outsourcing had yet a very strong negative impact accounting for 25 percent of the decline in the employment share of this group of workers.

Turning to UK, Hijzen et al. (2005) investigated the impact of international outsourcing on the skill structure of labor demand for three skill groups. This study departed from the previous approach adopted in Feenstra and Hanson (1996; 1999) and Strauss-Kahn (2003). The study estimates a system of four equations for variable factor costs combining SUR estimation techniques with panel data. The authors conclude that international outsourcing is a fundamental component in explaining the evolving skill structure of labor demand in UK. International outsourcing is found to have a strong negative effect on labor demand for all type of laborers, and in particular for unskilled workers, but a positive effect on demand for materials. The research clearly demonstrated that the negative impact of international outsourcing is stronger the lower the level of professional skills.

Recent contributions have started to use data collected by the World Input Output Database (see Timmer 2012). Foster et al. (2012) focused on offshoring and the elasticity of labor demand for a sample of 40 countries in the period from 1995 to 2009. Using broad and narrow offshoring measures both for manufacturing and service industries, the research employed a conditional and unconditional labor demand to find out that offshoring has an overall neutral or slightly positive effect on employment. In a further analysis, the paper provides evidence of differences across industry types and employment categories. Negative effects appear for service offshoring in low-skilled and high-skilled service industries whereas positive effects of offshoring appear in high-tech manufacturing industries for high-qualified workers (Foster et al. 2012a).

In a following paper, De Vries et al. (2012) examine the effect of broad and narrow offshoring on the skill structure of labor demand for 40 countries over the period from 1995 to 2009. Similar to Hijzen et al. (2005), the paper adopts a system of three variable factor demand equations (SUR) to find out that both narrow and broad offshoring measures reduce the relative demand for all type of skill-groups, especially in the manufacturing industries. From a closer perspective, it appears that medium-educated workers have paid the highest price whereas the remaining skill-categories are left relatively untouched by offshoring dynamics in the service industry.

As this section highlighted, studies that analyzed the impact of offshoring on employment recurred to a basic classification of skilled versus unskilled workers. In this work, a much more detailed classification of professional categories obtained from the Labor Force Survey (LFS) is proposed. Furthermore, while many studies have proposed a traditional division between broad and narrow offshoring, the additional offshoring indicators proposed here highlights the technological content of offshored goods relying on the technological level of the industry from which goods are sourced. The next section provides a detailed presentation of data and econometric strategy used in performing the empirical analysis.

3. Data and Econometric Strategy

3.1 Data

This section describes the dataset used for the econometric estimation. It also presents first descriptive evidence of the offshoring trends in the five economies under investigation. This research focuses on five European countries, namely Germany, Spain, France, Italy and United Kingdom. This study decided to focus on a relatively small group of European countries mainly for two reasons. First, data sources from which statistical information are drawn have the wider coverage level for this relatively small set of countries. Second, the selected countries reflect similar industrial dynamics that make the aggregated analysis consistent. Offshoring volumes are not dissimilar between countries and follow a rather similar evolution over time. Moreover, this group of countries has shown a very strong data reliability. Data stability has been proven by previous studies that have used the same group of countries (see Cirillo 2014).

Data are obtained from the Sectoral Innovation Database (SID) initially collected at the University of Urbino (see Lucchese and Pianta (2011) for the methodological notes on the construction of the database). This database includes 21 manufacturing sectors (from sector 15 to sector 36) and 17 service industries from (from sector 50 to sector 74) classified according to the international two-digit classification NACE Rev. 1 (see Table 1 in the Appendix for the list of sectors). The SID contains detailed information on innovative activities of sectors, economic performances, education and professional qualification combined from different international data sources (Eurostat Community Innovation Survey CIS and Labor Force Survey LFS, OECD Structural Analysis survey STAN, WIOD Socio-Economic Account SEA).

Data used for this work represents only a small portion of the amount of information contained in the SID. In order to avoid outliers, it was decided to drop industry 23 (i.e. Coke, Refined Petroleum and Nuclear Fuel) because its economic activity is not closely related to offshoring dynamics. Monetary variables obtained from SEA and WIOD have been deflated using the respective sectoral value added deflator provided in the SEA database. Data extracted from I-O tables are converted using the official euro/dollar exchange rates obtained from the International Monetary Fund (IMF) website. Monetary variables from SEA are expressed with their respective national currency. For this reason, only United Kingdom had to be converted from British pounds into euros using the exchange rate expressed in purchasing power parity (PPP).

Empirical studies investigating the impact of offshoring on employment and wages used both firms level and industry level data. In this work, industry level data are considered the right level of analysis, mainly for three reasons (see also Guarascio et al. 2015 for a similar explanation). First, datasets based on micro-level data are usually not representative of the universe of reference and results are hardly generalized to the whole economy. On the contrary, sectoral level data highlight the structural change undergone by the economy so that results are easily extendable to the aggregate analysis or assumed to be relevant for the economy as a whole. Second, technological factors are better captured by industry level analysis rather than by firms level studies where technological characteristics are inadequately represented. Firms in the same industry are very likely to share similar characteristics in terms of technological opportunities and market dynamics, factors that make the aggregate analysis representative and consistent. Third, demand dynamics are better identified by industry level data. In period of economic recession, single firms can have positive growth rates that do not reflect the general economic contingency. Industry level data offer a better appreciation of the general economic conditions despite the performance of the single economic unit. A further element that justifies the choice of this particular level of analysis is certainly the wide adoption of industry level intermediate inputs in the construction of the offshoring indicators.

Employment and Wages

Employment data are obtained from the Eurostat LFS database. LFS provides data information on occupation and educational level from 1999 to 2011 based on the ISCO88COM nomenclature. Four macro groups are then created, namely managers, clerks, craft workers and manual workers. This approach follows previous work on employment categories and innovation by Cirillo (2014). LFS data were also converted from NACE Rev. 2 into NACE Rev.1 through the use of a conversion matrix (see also Cirillo and Perani (2015) for further detail on the construction of the conversion matrix). The following table summarizes the typology of workers included within each macro professional group.

Table 1. Typology of Employees by Professional Group.

Macro Professional Groups	ISCO88Classification
MANAGERS	Legislators, Senior Officials and Managers, Professionals, Technicians and Associate Professionals
CLERKS	Clerks, Service Workers, Shop and Market Sales Force
CRAFT WORKERS	Skilled Agricultural and Fishery Workers, Craft and Related Trades Workers
MANUAL WORKERS	Plant and Machine Operators, Assemblers, Elementary Occupations

Source: Cirillo 2014.

The aggregation of LFS data on ISCO basis in four professional groups is motivated by two reasons. First, the skill content of the professions contained in each macro-group, intended here as the ability to carry out specific duties and tasks, correspond to the skill-level provided by the ILO classification system (ISCED). Second, professions included in each macro-group have similar gross earning patterns. Cirillo (2014) provides detailed analysis on the aggregation procedure and its consistency. Cirillo (2014) also performed a factorial ANOVA test to check whether the variability of employment shares by professional categories is driven by the industry, the time or the country dimension. Results show that the sectorial dimension is the most influential source of variability for the each professional group followed by the country and time dimension.

Data on wages are not directly available from data sources but are easily obtained from available information. First, a variable measuring the general labor cost is calculated. This piece of information is obtained by diving total labor compensation by the number of employees in the industry. Both elements are included in the original SEA database. A similar procedure for the calculation of wages by educational group is followed. The SEA database contains relevant information on total labor compensation and on the wage share by educational categories from which it is possible to back-calculate individual wage levels. Data available in WIOD SEA follow ISCED nomenclature. The ISCED framework organizes statistical information on the basis of the educational level attained by the worker. The SEA database include information on three educational groups based on ISCED categories: "low-skilled" for workers with lower secondary education, "medium-skilled" for workers with upper secondary education and "high-skill" workers for workers with university and post-university education. The total wage bill of each skill group is obtained by multiplying total labor compensation by the corresponding wage share. The total wage bill is then dived by the number of workers with the corresponding educational level although employment variables follow ISCO nomenclature. More precisely, the wage bill for high, medium and low skilled employees is divided respectively by the number of managers, clerks and manual workers.

Innovation

Innovation variables in the SID are drawn from the Eurostat Community Innovation Survey. CIS variables describe the evolution of industry technological patterns through several variables that measure the expenditure on innovation, the effects and the sources of the innovative process. The quality and the stability of the CIS innovation variables have been extensively tested (see for example Bogliacino and Pianta 2010). These variables are widely used in the literature (Bogliacino and Pianta 2013a; 2013b; Guarascio et al. 2015). For this research were considered innovation data from CIS 3 (1998-2000), CIS 4 (2002-2006) and CIS 6 (2006-2008). CIS 6 variables have been converted from NACE Rev. 2 into NACE Rev. 1 applying the same conversion matrix used in Cirillo (2014). This work uses two technological variables from the SID, precisely "share of firms introducing innovation" and the "share of firms aiming at reducing labor costs".

These two variables can be considered good proxies for *technological competitive* strategies, strategies aiming at developing and producing new products to open up new markets, and *cost competitive* strategies, targeted to increase profit by reducing production costs. This approach builds on previous work carried out by Pianta (2001) and Pianta and Bogliacino (2010) where the difference between technological and cost competitiveness is investigated using the very same set of CIS innovation variables. Cirillo (2014) performed a factorial ANOVA analysis to check weather time, country and industry dimension are driving variance in technology variables. The analysis found out that the industry dimension explains the variance in the share of firms introducing innovation whereas the temporal dimension helps to explain the variation in the variable measuring the share of firms that reduce labor costs through the introduction of new technologies. The following table provides first descriptive evidence of technological patterns for the five countries under investigation. It is possible to notice that Germany has the largest share of innovators both in the manufacturing and service sector followed by France, Italy and UK. UK has also the largest share of firms whose innovative strategy aims at reducing labor cost, both in manufacturing and service industry. Table 2 the industry average across the three waves of the Community Innovation Survey used in this work.

Table 2. Descriptive Statistics for Innovation Variables.

Country	Industry	Share of Innovators	Firms reducing labor costs
Germany	*Manufacturing*	64.58	19.56
	Service	57.65	15.30
Spain	*Manufacturing*	37.90	11.90
	Service	32.46	9.54
France	*Manufacturing*	43.01	17.83
	Service	36.28	10.74
Italy	*Manufacturing*	42.68	13.58
	Service	30.63	7.379
United Kingdom	*Manufacturing*	42.09	33.40
	Service	32.21	22.59

Source: Own Illustration.

Economic Performance and Offshoring

The last group of variables provides industry-level information on economic performances. Data for value added are directly available from the SEA dataset. Labor productivity is calculated by dividing value added by the number of hours worked in the sector. Data for the construction of the offshoring indicators are extracted from NIOT tables. Additional details on the construction of I-O tables in WIOD are provided in Timmer et al. (2012). Data obtained from WIOD are adapted to the same NACE level used in the rest of the SID. Sectors Agricultural, Hunting and Forest (AtB), Mining and Quarrying (C), Electricity and Water Supply (E), Construction (F) are omitted from the construction of the database. Sector from L to P referring to Public Sector Administration and Defense, Education, Health and Social Work, Community and Social Services and Private Households with Employed Personnel are not included in the rest of the SID and for this reason are omitted from the research. Sector 17t18, 21t22, 27t28, 30t33, 34t35, J and 71t74 are disaggregated to the comparable industry level followed in the rest of the SID. Data are disaggregated thanks to specific sectoral employment weights assigned to the underlying sectors. Weights are calculated as the share of workers in the disaggregated sector to total industry employment. Data are obtained from LFS surveys. In order to account for employment changes over the time, four weights are used (95-99, 99-03, 03-08, 08-11). Offshoring variables are calculated directly from the I-O tables. For this reason, it is not possible to follow the same disaggregation procedure. To match the information obtained from I-O tables to the level of disaggregation followed in the rest of the dataset, the same offshoring value is attached to the disaggregated sector.

The construction of offshoring indicators follows the methodology adopted in Feenstra and Hanson (1996; 1999). The broad offshoring indicator (named "inter-industry offshoring") measures the sum of non-energy imported intermediate goods over the sum total of intermediate goods, where by total is meant the sum of home and foreign purchased intermediate inputs excluded inputs from energy sectors. The narrow offshoring indicator (here named "intra-industry offshoring") restricts the numerator to the imports of intermediate goods from the same sector abroad. The differential offshoring indicator (here also named "inter-industry offshoring") is a variant of the broad offshoring index and is the simple arithmetic difference between the broad and the narrow offshoring indicator.

$$Inter - Industry = \frac{\sum_k \sum_{jk} m^i_{j\neq k}}{\sum_k \sum_j (d^i_{jk} + m^i_{jk})} \qquad Intra - Industry = \frac{\sum_k m^i_{j=k}}{\sum_k \sum_j (d^i_{jk} + m^i_{jk})}$$

The construction of the high-tech and low-tech offshoring indicator follows the same logic. In the construction of the high-tech offshoring indicator, the numerator includes intermediate inputs imported exclusively from foreign high-tech sectors. Likewise, the low-tech offshoring indicator includes intermediate inputs imported exclusively from foreign low-tech sectors. The classification of industries in high-tech and low-tech sectors relies on the classification of industries originally proposed by Pavitt (1984). Pavitt identified four groups of industries on the basis of the peculiar technological, productive and market characteristics. The four groups are Science-Based industries (SS), Specialized-Supplier industries (SS), Scale and Information Intensive industries and Supplier Dominated (SD) industries. Bogliacino and Pianta (2010) provide a more detailed description of the economic and technological for each Pavitt class. The original Pavitt taxonomy included only manufacturing sectors. Pianta and Bogliacino (2010) extended the Pavitt taxonomy to service industries on the basis of information on the sectoral-level technological activity contained in Eurostat innovation surveys. Low-tech offshoring measures the quantity of imported inputs from foreign low-tech sectors that belongs to Scale-Intensive and Science-Dominated classes. High-tech offshoring include the import of intermediate inputs from foreign Science-Based and Specialized Supplier industries. Table 1 in the Appendix provides a detailed list of the 38 NACE Rev. 1 industries classified according to the Revised Pavitt Taxonomy. This innovative approach allows adding a new qualitative dimension to the construction of the offshoring indicator that will be of particular interest in the following empirical investigation. Table 3 summarizes the different data sources and time period used in this work.

Table 3. List of Data Sources.

Data	Sources	Periods
Innovation Variables	Eurostat Community Innovation Survey (CIS)	CIS 3 (1998-2000) CIS 4 (2002-2004) CIS 6 (2006-2008)
Economic performance	WIOD Socio-Economic Account (SEA)	From 1999 to 2011
Offshoring Variables	NIOT Input-Output Tables (WIOD)	From 1999 to 2011
Professions and education (ISCO)	Eurostat Labor Force Survey (LFS)	1999, 2000, 2003, 2005, 2006, 2007, 2009, 2011
Wages and Hours Worked (ISCED)	WIOD Socio-Economic Account (SEA)	From 1999 to 2011

Source: Own Elaboration

The final database is a pooled cross-section that is constructed by merging three different time period 2000-2003, 2003-2007 and 2007-2011. This procedure allows obtaining two major advantages. First, it is possible to control whether the economic relationship under investigation holds during phases of economic growth and phases of economic depression. This was the case for the period from 2007 to 2011 and to a minor extent from 2000 to 2003. Second, by pooling three different cross-sections, it is possible to increase the number of observations available for the econometric analysis so that the model can be eventually tested on a restricted group of observations without compromising the reliability of the results. Employment, wages, and economic performance variables are expressed in rate of variation. Rate of variation is computed as compound annual rate of growth for each sub-period. This procedure approximates the utilization of logarithmic differences that are widely used in econometric studies on offshoring. The compound annual growth rate is calculated by using the following formula where *n* stands for the number of years in the sub-period:

$$CARG = \left(\frac{x_t}{x_{t-1}}\right)^{\left(\frac{1}{n}\right)} - 1$$

3.2. The determinants of employment and wages: the models

The approach followed in this paper departs from previous models used in the offshoring literature. In order to explore the relationship between employment, wages and offshoring this research builds on the previous work of Bogliacino and Pianta (2010) and Cirillo (2014) that analyzed the impact of divergent technological patterns on employment. These models combine elements from the Keynesian tradition that emphasize the role of demand in driving employment growth and from the Schumpeterian school that root economic growth in the technological endeavor in the supply side of the economy.

Technology is driving structural change in advanced economy. Although technology is often seen as an undifferentiated process affecting employment, Pianta (2001) suggests a key distinction between technological competitiveness and cost (or price) competitiveness that is further developed and tested by a number of contributions (Bogliacino and Pianta 2010; Crespi and Pianta 2008; Pianta and Tancioni 2008). This approach is firmly rooted in the theorical framework delineated almost a century ago by the Austrian economist Joseph Schumpeter. Schumpeter distinguished between product and process innovation. Product innovation strategies consist in the creation of new and better goods that stimulate firms' output growth. On the contrary, process innovation strategies lower production costs through the application of more efficient technologies that allow firms to reduce prices and in turn to increase sales.

Bogliacino and Pianta (2010) made a consistent effort to show that strategies of technological competitiveness and costs competitiveness exert contrasting effects on employment. The former, associated with product innovation strategies, requires that firms are strongly oriented towards overall innovative activities such as research and development, designing, investment in new equipment and machineries. These strategies are expected to yield a positive effect on employment growth thanks to the incentives that new product could have on firms' sales. The latter, implies that firms innovative efforts are focused around strategies aiming at increasing efficiency including labor saving technologies and technology increasing production flexibility. Such strategies are expected to negatively effects employment growth as more efficient production techniques tend to decrease the number of workers required in the production process. The study confirmed the expected results. Technological competitiveness has a significant and positive effect on employment whereas cost competitiveness has a negative effect on labor. The model was also tested in subsets of industries that correspond to a taxonomy of Revised Pavitt classes and found that technology has a different impact on employment (measured by the number of hours worked) for each subgroup. In Science Based industries, cost competitiveness has no significant effect whereas technological competitiveness positively influence the rate of growth of hours worked. In Specialized Supplier industries the creation of new products has a small positive effect and labor saving process and a strong negative effect on the number of hours worked. In Scale and Information Intensive industries and Supplier Dominated industries, labor saving technology and wages led to an overall decline of employment although counterbalanced by the positive effect of demand.

Cirillo (2014) tested the model on the four professional groups presented in the descriptive section above. The study investigated the impact of technological competiveness and cost competitiveness on the workforce composition. Employment subdivision in four macro professional groups has been thoroughly explained. The research found a positive effect of product innovation and a negative effect of cost competitiveness technology on all professional groups although from a closer look it appears that in manufacturing industries the effect of technological innovation both in terms of process and product innovation is much more pronounced for managers and manual workers.

Bogliacino and Pianta (2013a) deployed a system of three simultaneous equations to show how R&D intensities, innovative turnover and profit growth, are genuinely intertwined in a positive self-reinforcing loop that from higher R&D expenditure and better technological improvement is capable of generating higher profits. In a following paper, Bogliacino and Pianta (2013b) extended the model in order to include the effects of different demand factors (export, domestic consumption, and intermediate demand) and of different innovation strategies (cost competitiveness and technological competitiveness). The authors found different role for different demand proxies and technological strategies. Product innovation is positively associated to export growth while intermediate and household consumption do not seem to have the same positive influence. Firms selling product in domestic less competitive markets rely on output generated domestically and might be less incentivized to invest in new products and expand towards new foreign markets.

Guarascio et al. (2015) added a new dimension to the models originally proposed by Bogliacino and Pianta (2013a; 2013b). The paper included the additional link between R&D expenditure, innovation and export success. Results confirm the existence of a virtuous circle connecting higher R&D expenditure, the increase in the industry share of product innovators and the expansion of the export market share. The paper found also strong differences between a sub-group of Northern countries (Germany, the Netherlands and UK) and a sub-group of Southern countries (Italy, Spain and France). While the former seems to profit from the positive link between innovation and international competitiveness, the latter is unable to catch up with innovation and for this reason is deemed to lose international competitiveness.

The model proposed here builds upon this theoretical as well as empirical background adding the new offshoring element to the model. The novelty of this approach resides in the fact that offshoring is no longer distinguished exclusively between broad and narrow offshoring. The innovation here is to characterize offshoring according to the technological level of the sector from which the intermediate input is sourced. In the first model, employment depends on technological and costs competitiveness factors, labor cost, demand, and the level of offshoring. The model yields the following equation:

$$\Delta EMP_i = \beta_0 + \beta_1 \Delta DEM_i + \beta_2 \Delta W_i + \beta_3 TC_i + \beta_4 CC_i + \beta_5 OFF_i + \beta_6 OFF_i + C + T + \epsilon_{i,t} \quad (1)$$

In equation 1 above, ΔEMP_i indicates the compound annual rate of change in total employment, ΔDEM_i is the compound annual rate of growth of sectoral value added used as a proxy for demand, ΔW_i is the compound annual rate of change of labor compensation, TC_i and CC_i indicates respectively technological and cost competitiveness variables and OFF_i stand for the offshoring variables. The variable ΔEMP_i is replaced in turn by the growth rates of employment by occupational categories, namely managers, clerks, craft and manual workers as in Cirillo (2014). Since the model is estimated at the industry level, the subscript *i* stands for the industry.

$$\Delta W_i = \beta_0 + \beta_1 \Delta PROD_i + \beta_2 \Delta EMP_i + \beta_3 TC_i + \beta_4 CC_i + \beta_5 OFF_i + \beta_6 OFF_i + C + T + \epsilon_{i,t} \quad (2)$$

In equation 2, ΔW_i represent the rate of growth of the individual wage. In a first step, the model is estimated for a general labor cost variable then for the individual wage divided by educational group. The variable $\Delta PROD_i$ indicates the rate of change in productivity growth that is considered here to be a good proxy for demand. This variable is then substituted by the compound annual rate of growth of industry value added, just as in equation 1. The employment rate of variation ΔEMP_i is replaced in turn by the rate of change for the correspondent professional group.

Variables *C* and *T* represents respectively a set of country and time-dummy variables. The five countries under investigation differ strongly in terms of industrial relations, labor market institutions, welfare institutions and other industrial and economic characteristics. Country dummy variables are included to check whether the relationships hold when specific country effects are accounted. Variable *T* indicates a set of three temporal dummy variables. Since the final database is a pool of three single cross-sectional datasets (corresponding to three variation in time 00-03; 03-07; 07-11) each temporal dummy variable stands for each subgroup of observations. Including temporal dummy variables in the regression allow the intercept to shift across time in order to reflect the different distribution of the observation across the different periods. The pattern of the coefficients for the dummy variables might be of some interest by itself. This would indicate the temporal evolution of the dependent variable in the model.

In the two equations above, offshoring variables are always included in pairs. The two pair of offshoring variables included in the model are respectively inter-industry (differential) and intra-industry (narrow) and high-tech and low-tech offshoring. Including offshoring variables in this fashion does not raise multicollinearity issues since the information contained in the two indicators are different from each other. In the construction of the differential offshoring indicator, imported intermediate inputs from the same sector abroad are not included. This allows the information contained in the intra-industry indicators to be captured in isolation by the narrow offshoring variable. There is a very low degree of correlation between the differential and the narrow offshoring indicator (correlation coefficient 0.1441) and a slightly negative correlation between the high-tech and low-tech offshoring index (-0.0421). For the complete correlation matrix see Table 2 in the Appendix.

In equation 1, value added is expected to have a positive effect on aggregate employment and on employment subdivided by professional groups. Technological and cost competitiveness strategies are expected to have contrasting effects. Technological innovation, represented by the variable indicating the share of firms in the sector introducing some sort of product innovation, is expected to have an overall positive effect on employment. Thanks to higher sales and higher returns, product innovation is expected to have an overall positive effect on employment. However, given the vagueness in the definition of the innovative effort, it is possible that the variable would instead captures a much more general process of technological innovation that might overlap other innovative strategies, such as cost competitiveness innovation. Although its effect is expected to be positive, it would not be surprising to obtain a negative coefficient for this variable. On the contrary, cost competitiveness strategies represented in the regression by the share of firms introducing innovation in order to reduce labor costs are expected to have a negative effect on employment. However, this relationship may not be true for some professional categories that thanks to their professional position and technical skills could benefit from a general competitive strategy aiming at reducing labor cost. As the neoclassical theory suggests, labor cost is expected to have e negative effect on employment across all professional groups. Offshoring is expected to have a negative effect on employment, and possibly even a more pronounced negative impact on less sophisticated professional categories. This interpretation is consistent with the vision of offshoring replacing domestic with foreign jobs.

The same reasoning applies for equation 2 where the wage bill is a function of technological and cost competitiveness factors, demand, the employment rate of growth and the offshoring level. Productivity is expected to have an overall positive impact on the wage bill as well as the growth in valued added. Higher technology competitiveness factors are expected to yield a positive effect on the wage level. Conversely, cost competitiveness factors are expected to decrease the wage premium. However, it is likely to expect an increase in the wage premium of the remaining workers when firms get rid of less productive and more labor intense production stages. The variation in the number of workers is expected to have a potential negative effect on the wage level as the neoclassical theory suggests. Although it is easy to predict a potential negative effect of offshoring on employment, particularly for lower qualified occupations, predicting the effect of offshoring on wages is a much more difficult task. The idea here is that a certain type of offshoring might in effect raise the wage bill for certain groups of workers, especially when the content of the offshoring production complements production carried out in the home industry. By contrast, offshoring may very well hinder wage growth for less skilled worker groups, especially when the content of offshore production substitute production previously performed in the home industry. This interpretation follows the idea that wages for some categories of workers have now to compete in a global market where cheap labor in developing economies and unregulated labor markets can drive down the wage premium for low-qualified workers in industrialized economies. Table 4 resumes the variables used for the econometric analysis as well as the various sources of origin.

Table 4. List of Variables and Original Data Sources.

Variables	***Original Source***
Value Added Growth	WIOD SEA
Productivity Rate of Change	WIOD SEA
Labor Cost Rate of Change	WIOD SEA
Share of Firms Performing Innovation	CIS
Share of Firms Innovating Reducing Labor Cost	CIS
Rate of Growth Wages Low-Education Workers	WIOD SEA
Rate of Growth Wages Medium-Education Workers	WIOD SEA
Rate of Growth Wages High-Education Workers	WIOD SEA
Total Employment Rate of Change	LFS
Managers Rate of Change	LFS
Clerks Rate of Change	LFS
Craft Workers Rate of Change	LFS
Manual Workers Rate of Change	LFS
Inter-Industry Offshoring (Differential)	WIOD NIOT
Intra-Industry Offshoring (Narrow)	WIOD NIOT
High-Tech Offshoring	WIOD NIOT
Low-Tech Offshoring	WIOD NIOT

3.3. The econometric strategy

After having presented the theoretical insights on technology, wages, offshoring and employment, in this section the analysis turns to the empirical investigation of the relationship between the afore mentioned variables. The following simple labor demand curve can be used as baseline equation for the model:

$$y_i = x_i^{'} \beta + u_i + v_i$$

In the equation above, y_{it} represent the employment variable, x_{it} indicates the vector of regressors, u_i the individual effect and v_{it} the random disturbance where the subscript *i* stands for the industry. The equation above can be assumed to be a standard firm's translog cost function where both dependent and independent variables are expressed in log-scale. The individual effect is eliminated by taking the first difference of the equation above:

$$y_{i,t} - y_{i,t-1} = \beta \left(X_{i,t} - X_{i,t-1}\right) + (u_i - u_i) + (v_{i,t} - v_{i,t-1})$$

$$\Delta y_{i,t} = \beta \Delta X_{i,t} + \Delta u_{i,t}$$

Since the log difference approximate the variation in rate of changes, it is possible to express both regressors and regressand as rate of growth. As mentioned above, compound rates of change are computed instead of taking the normal long difference. Innovation and offshoring variables are included in the model in percentage point referring to the first year in the variation period. In this way, offshoring and innovation variables make reference to a one year period thus emphasizing the lagged impact of technology and production fragmentation on home employment and wages. Moreover, innovation variables represent the share of firms in the sector performing a certain type of innovation. The variables are a good proxy for the innovative strategy as they capture the technological level deployed in the industry. The model can be estimated using OLS regression techniques. However, since the observations (i.e. industries) differ strongly in size and the OLS treats all observations as equal, Weighted Least Squares (WLS) estimation techniques are used. Weights used in the regression are calculated as the arithmetic average of the employment variable from 1999 to 2011. Since heteroskedasticity is a common problem with monetary variables and more in general with variables in level form, in the regressions robust standard errors are applied. The problem of heteroskedasticity is also partly eliminated by transforming level variables in growth rates. The robustness of the results is proven by additionally testing the model on a subgroup of manufacturing industries.

Table 5 report preliminary summary statistics for all variables. It is easily noticeable that the number of observations differs greatly between variables. By construction, variables collected from WIOD should contain 555 observations (obtained from merging three cross-sectional databases with 37 industries for 5 countries). Other variables (technological variables from CIS and employment variables from LFS) contained already some missing values. Before running the regressions, outlying observations were carefully removed from the dataset. OLS and WLS estimation techniques are susceptible to outlying observations. Broadly speaking, outliers are those observations that change the OLS estimates by a considerable amount. Outliers were removed after having computed summary statistics when they clearly deviated from the rest of sample.

Table 5. Descriptive Statistics for all Variables.

Variables	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Value Added Growth	546	.7137306	4.194117	-14.62213	14.95683
Share of Firms Performing Innovation	520	41.8927	18.20544	.2267319	89.44954
Share of Firms Innovating Reducing Labor Cost	514	16.71945	13.00798	1.005025	68.68124
Labor Cost Rate of Change	540	.6080381	6.312794	-19.5806	19.18827
Wage Growth Low-Education Workers	528	1.532462	13.96148	-49.58971	48.31767
Wage Growth Medium-Education Workers	539	3.209906	10.17455	-39.20387	38.66804
Wage Growth High-Education Workers	547	.7837657	9.691713	-37.76177	32.09653
Total Employment Rate of Change	549	-.6204751	5.718358	-18.719	18.7831
Managers Rate of Change	553	2.114471	8.657952	-39.28889	33.39157
Clerks Rate of Change	552	-1.254676	10.2758	-49.51129	44.06644
Craft Workers Rate of Change	498	-2.792685	10.4942	-34.38258	33.28563
Manual Workers Rate of Change	532	-1.809372	12.11213	-49.09433	45.2272
Inter-Industry Offshoring (Differential)	555	.1111391	.0532076	.029315	.3356279
Intra-Industry Offshoring (Narrow)	555	.0805643	.077229	.0000238	.3178088
High-Tech Offshoring	555	.0961371	.0800132	.0109985	.3519999
Low-Tech Offshoring	555	.0932857	.0645724	.0132817	.3644165

Source: Own Elaboration

4. Results

The model for total employment

Table 6 reports the results of the regression on total employment growth. Equations one and two include inter-industry (differential) and intra-industry (narrow) offshoring while equations three and four introduce low-tech and high-tech offshoring. Both models are tested with and without country-dummy variables. Value added growth and labor compensation coefficients confirm expectations. Value added growth has a positive and statistically significant impact on total employment growth while labor compensation has a negative and statistically significant effect. The share of firms performing innovation has a positive and statistically significant coefficient at the 10 percent significance level only when country dummy are excluded from the model. By contrast, and very much in line with expectations, the variable representing the share of firms in the industry introducing labor saving technology is found to have a negative and statistically significant effect on employment growth when country dummy variables are not included.

The fact that innovation variables are not statistically significant when the country-dummies are included in the model is a result by itself. This means that offshoring and innovation, both in terms of product and process innovation, have different effects across different countries. This is an interesting result that could confirm the findings in Guarascio et al. (2015) where Northern and Southern European countries are found to adopt different technological strategies. Results also confirm previous findings of Bogliacino et al. (2010) that found opposite sign for technological competitiveness and cost competitiveness strategies.

Offshoring coefficients largely reflect expectations according to which offshoring substitutes domestic with foreign jobs (OECD 2007; Milberg and Winkler 2013). All offshoring coefficients are negative and statistically significant for all model specifications. It is also possible to say that inter-industry and low-tech offshoring have a much larger negative impact than intra-industry and high-tech offshoring. This is probably due to the fact that a larger amount of intermediate imported inputs substitutes for a larger share of otherwise domestically produced inputs. Similarly, the increasing import of low-tech inputs substitutes the production of less advanced domestic industries. Providing a mathematical interpretation to the coefficient, it is possible to say that keeping everything else constant, in the first equation, one percent increase in inter-industry offshoring yields a 0.18 percent decrease in employment growth. A pattern also emerges when looking at temporal dummy coefficients.

The temporal-dummy coefficients show that keeping everything else equal, there is a positive return on industry employment growth in the periods from 2000 to 2003 and from 2003 to 2007 with respect to the period dropped 2007-2011, characterized by the Great Recession.

Table 6. Determinants of Total Employment Change.

Dependent Variable: Change in Total Employment Growth	(1)	(2)	(3)	(4)
Value Added Growth	.2330	.3335	.2071	.3023
	(.0696)***	(.0696)***	(.0755)***	(.0759)***
Labor Compensation per Employee	-.1282	-.1504	-.1224	-.1438
	(.0466)***	(.0471)***	(.0474)***	(.0480)***
Share of Firms Performing	.0262	-.0028	.0275	-.0039
Innovation	(.0148)**	(.0172)	(.0147)*	(.0169)
Share of Firms Innovating Reducing	-.0771	-.0206	-.0767	-.0193
Labor Costs	(.0213)***	(.0202)	(.0210)***	(.0193)
Inter-Industry Offshoring	-.1575	-.1541		
	(.0395)***	(.0402)***		
Intra-Industry Offshoring	-.0938	-.0871		
	(.0344)***	(.0329)***		
High-Tech Offshoring			-.0965	-.0848
			(.0307)***	(.0305)***
Low-Tech Offshoring			-.1537	-.1558
			(.0463)***	(.0460)***
Constant	1.203	1.613	.9532	1.328
	(.7989)	(.8740)*	(.7350)	(.7907)*
Time Dummy_0003	1.906	1.645	1.932	1.677
	(.6611)***	(.5949)***	(.6625)***	(.5971)***
Time Dummy_0307	2.053	1.913	2.106	1.984
	(.7097)***	(.6369)***	(.7128)***	(.6452)***
Time Dummy_0711	(omitted)	(omitted)	(omitted)	(omitted)
Country Dummy	No	Yes	No	Yes
$\mathbf{R^2}$	0.22	0.27	0.22	0.27
N. Obs.	488	488	488	488

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

Table 7 reports the results of the regressions on the subsample of manufacturing industries where offshoring practices are most important. Results are broadly in line with findings above with the only exception that the coefficient of the cost competitiveness variable (share of firms innovating reducing labor cost) has a positive sign. In this case, results obtained are quite surprising and in contradiction with the general findings of previous studies presented above that did not differentiate between manufacturing and service industries (Bogliacino et al. 2013a; Cirillo 2014). Cost competitiveness strategies seem to have a positive and statistically significant effect on the employment rate of growth but only when country-dummy variables are included in the model. One possible explanation could be that all countries adopt a similar strategy for which technological innovation aimed at optimizing labor costs favors certain professions more than others and that in manufacturing industries it has an overall positive effect on total employment growth.

Table 7. Determinants of Total Employment Change in Manufacturing Industries.

Dependent Variable: Change in Total Employment Growth	(1)	(2)	(3)	(4)
Value Added Growth	.2863	.3478	.2924	.3583
	(.0846)***	(.0851)***	(.0836)***	(.0844)***
Labor Compensation per Employee	-.1090	-.0918	-.1093	-.0942
	(.0426)**	(.0450)**	(.0413)***	(.0442)**
Share of Firms Performing	.0651	.0443	.0668	.0685
Innovation	(.0184)***	(.0287)	(.0201)***	(.0338)**
Share of Firms Innovating Reducing	-.0160	.0434	-.0150	.0407
Labor Costs	(.0180)	(.0220)**	(.0171)	(.0217)*
Inter-Industry Offshoring	-.1986	-.1461		
	(.0458)***	(.0459)***		
Intra-Industry Offshoring	-.1136	-.0884		
	(.0372)***	(.0399)**		
High-Tech Offshoring			-.1507	-.1306
			(.0364)***	(.0413)***
Low-Tech Offshoring			-.0984	-.0567
			(.0476)**	(.0483)
Constant	-.1922	-1.381	-1.123	-3.623
	(.9990)	(1.847)	(1.145)	(2.263)
Time Dummy_0003	.6334	.2305	.6160	.3063
	(.5757)	(.5846)	(.5791)	(.6049)
Time Dummy_0307	(omitted)	(omitted)	(omitted)	(omitted)
Time Dummy_0711	-.5253	-.3078	-.7019	-.4851
	(.7099)	(.7271)	(.7057)	(.7250)
Country Dummy	No	Yes	No	Yes
$\mathbf{R^2}$	0.19	0.24	0.18	0.24
N. Obs.	286	286	286	286

Weighted Least Squares with Robust Standard Errors in Parenthesis

* significant at the 10% level

** significant at the 5% level

***significant at the 1% level

The model for professional groups

Another finding departs from the results of the regression on the full sample of industries. Although high-tech and low-tech offshoring coefficients maintain negative signs, the magnitude of the two offshoring coefficients is inverted. It appears that in manufacturing industries, high-tech offshoring decrease employment more than low-tech offshoring. It is also to note that the low-tech offshoring coefficient is not statistically significant when country-dummies are included. Further analysis is provided with the following tables where the model is tested on four different professional groups. Goal of the analysis is to show how the impact of innovation and offshoring on employment depends also on the underlying task performed by the worker, i.e. the professional group to which workers belong.

Table 8 reports the results for the regression on the managers rate of growth. Value added growth seems to be positive and statistically significant only in manufacturing industries whereas labor cost negatively affects the managers rate of growth only in the full sample of industry. Since none of the offshoring indicator has a statistically significant coefficient, managers seem not be influenced by the increase in international fragmentation of production.

Table 8. Determinants of Change in Managers.

Dependent Variable: Change in Managers Rate of Growth	(1) ***All Industries***	(2) ***All Industries***	(3) ***All Industries***	(4) ***Manufacturing***	(5) ***Manufacturing***
Value Added Growth	.0504	.1663	.2134	.4095	.42343
	(.1105)	(.1203)	(.1279)*	(.1326)***	(.1313)***
Labor Compensation per Employee	-.1698	-.1920	-.2105	-.0549	-.0615
	(.0848)**	(.0914)**	(.0930)***	(.0837)	(.0815)
Share of Firms Performing	-.0197	-.0125	.0049	-.1128	-.0822
Innovation	(.0248)	(.0302)	(.0314)	(.0424)***	(.0496)*
Share of Firms Innovating Reducing	-.1047	-.0411	-.0418	.1005	.0962
Labor Costs	(.0384)***	(.0471)	(.0464)	(.0325)***	(.0316)***
Inter-Industry Offshoring	-.0913	-.0684		-.0270	
	(.0656)	(.0704)		(.0850)	
Intra-Industry Offshoring	.0851	.0723		-.0417	
	(.0631)	(.0607)		(.0660)	
Offshoring High-Tech			-.0423		-.0734
			(.0518)		(.0635)
Offshoring Low-Tech			.0782		.0042
			(.0757)		(.0828)
Constant	6.717	3.759	2.093	7.574	5.647
	(1.212)***	(2.017)*	(2.128)	(3.012)	(3.693)
Time Dummy_0003	-.7622	-.7871	-.7301	-1.531	-1.410

	(.8994)	(.8017)	(.8115)	(.8787)*	(.8978)
Time Dummy_0307	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Time Dummy_0711	-3.601	-3.196	-3.217	.7223	.6354
	(1.364)***	(1.305)**	(1.304)	(1.197)	(1.200)
Country Dummy	No	Yes	Yes	Yes	Yes
R^2	0.09	0.12	0.12	0.16	0.16
N. Obs.	493	493	493	287	287

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

In table 8, coefficients of technological variables show counterintuitive signs in manufacturing industries (labor saving technologies positive and significant). These findings are partially confirmed from results of the regression on the next professional group. Table 9 below reports the results for the regression on clerks. Value added plays a major role in determining the rate of growth of clerks while labor compensation is not a discriminant for this category of workers. The increase in the share of firms performing labor saving innovation yields positive returns while all offshoring types seem to negatively impact this professional group.

Table 9. Determinants of Change in Clerks.

Dependent Variable: Change in Clerks Rate of Growth	(1) ***All Industries***	(2) ***All Industries***	(3) ***All industries***	(4) ***Manufacturing***	(5) ***Manufacturing***
Value Added Growth	.0824	.2121	.2106	.2620	.2826
	(.1124)	(.1016)**	(.1051)**	(.1517)*	(.1504)*
Labor Compensation per Employee	-.1129	-.1121	-.1133	-.0925	-.1028
(rate of growth)	(.0731)	(.0730)	(.0740)	(.0877)	(.0876)
Share of Firms Performing	.0731	-.0474	-.0445	-.0311	.0159
Innovation	(.0239)*	(.0316)	(.0309)	(.0527)	(.0612)
Share of Firms Innovating Reducing	-.0580	.0770	.0773	.1658	.1589
Labor Costs	(.0331)*	(.0424)*	(.0424)*	(.0514)***	(.0517)***
Inter-Industry Offshoring	-.1428	-.1798		-12.85	
	(.0942)	(.0846)**		(.1141)	
Intra-Industry Offshoring	-.1366	-.1276		-.1468	
	(.0594)**	(.0529)**		(.0863)*	
High-Tech Offshoring			-.1502		-.1948
			(.0614)**		(.0931)**
Low-Tech Offshoring			-.1476		-.0730
			(.0579)**		(.0945)
Constant	2.241	5.973	5.552	.8398	-2.243
	(1.290)	(1.628)***	(1.311)***	(3.532)	(3.978)
Time Dummy_0003	-1.797	-2.210	-2.180	.1954	.3785

	(1.188)	(1.060)**	(1.045)**	(1.213)	(1.236)
Time Dummy_0307	-1.340	-1.496	-1.457	(omitted)	(omitted)
	(1.117)	(.9792)	(.9767)		
Time Dummy_0711	(omitted)	(omitted)	(omitted)	3.709	3.549
				(1.468)**	(1.444)**
Country Dummy	No	Yes	Yes	Yes	Yes
R^2	0.06	0.15	0.15	0.13	0.13
N. Obs.	492	492	492	287	287

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

Table 10. Determinants of Change in Craft Workers.

Dependent Variable: Change in Craft Workers Rate of Growth	(1) ***All Industries***	(2) ***All Industries***	(3) ***All Industries***	(4) ***Manufacturing***	(5) ***Manufacturing***
Value Added Growth	.2284	.3824	.4047	.2316	.2605
	(.1875)	(.2046)*	(.2087)*	(.1234)*	(.1214)**
Labor Compensation per Employee	-.4188	-.4359	-.4465	-.1370	-.1472
	(.1308)***	(.1333)***	(.1373)***	(.0724)*	(.0677)**
Share of Firms Performing Innovation	-.0052	-.0246	-.0104	.0733	.1356
	(.0396)	(.0542)	(.0567)	(.0437)*	(.0466)***
Share of Firms Innovating Reducing Labor Costs	.0011	.0658	.0666	-.0069	-.0141
	(.0472)	(.0673)	(.0673)	(.0400)	(.0396)
Inter-Industry Offshoring	-.0831	-.1149		-.0703	
	(.1012)	(.1002)		(.0695)	
Intra-Industry Offshoring	.0990	.0121		-.0167	
	(.0732)	(.0748)		(.0593)	
High-Tech Offshoring			-.0758		-.1055
			(.0806)		(.0561)*
Low-Tech Offshoring			-.0156		.0654
			(.0848)		(.0712)
Constant	-1.493	1.040	.0385	-5.856	-9.027
	(1.954)	(2.400)	(2.326)	(2.264)***	(2.520)***
Time Dummy_0003	-.3313	-.8529	-.7786	-.2648	.2342
	(1.471)	(1.481)	(1.476)	(1.068)	(1.020)
Time Dummy_0307	1.474	1.126	1.155	.5179	.7967
	(1.704)	(1.757)	(1.750)	(1.036)	(.9838)
Time Dummy_0711	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Country Dummy	No	Yes	Yes	Yes	Yes
R^2	0.08	0.12	0.11	0	0.16
N. Obs.	446	446	446	287	279

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

Table 10 and 11 report results of the regression on workers with lower professional qualifications namely craft and manual workers. Valued added growth is a major component in determining employment growth for craft and manuals while on the contrary labor compensation is found to have a detrimental and statistically significant effect only on change of craft workers. It is very interesting to note that differently from managers and clerks, the increasing share of firms introducing labor saving technologies has a negative and statistically significant effect on manual workers. This finding certainly confirms expectations formulated above according to which it is likely that the implementation of strategies that optimize labor cost penalize more routinized professions while favoring others.
For the professional category of craft workers, offshoring coefficients are not statistically significant with the sole exception of high-tech offshoring in manufacturing industries. Results change dramatically for manual workers that are heavily affected by intra-industry offshoring and low-tech offshoring. Low-tech offshoring, in particular in equation three and five, has the largest coefficient so far encountered across all regressions. Everything else equal, it is possible to say that one percent increase in the low-tech offshoring indicator yields 0.35 percent decrease in the growth rates of manual workers in the full sample of industries and a .23 percent decrease in the sample of manufacturing industries. This result supports the view that sees offshoring replacing domestic production, especially in labor-intensive and less technologically advanced industries. The magnitude of intra-industry coefficient is also quite surprising. Probably, the penetration of narrow offshoring in domestic production substitutes for more jobs of less qualified workers.

To summarize, it is possible to say that: (1) none of the offshoring coefficient is statistically significant in the regressions on managers; (2) clerks are negatively affected by all types of offshoring and coefficients are statistically significant; (3) regressions on craft workers reveal no significant information of the impact of offshoring on this professional group with a single minor exception (high-tech offshoring in manufacturing industry); (4) manual workers are heavily impacted by low-tech offshoring and intra-industry offshoring both in the full sample and in manufacturing industries. It is possible to conclude that offshoring has a negative effect on employment, in particular on highly-routinized and labor-intensive tasks. In the next paragraph, the analysis turns to the investigation of innovation and offshoring on wages by different working categories.

Table 11. Determinants of Change in Manual Workers.

Dependent Variable: Change in Manual Workers Rate of Growth	(1) ***All Industries***	(2) ***All Industries***	(3) ***All Industries***	(4) ***Manufacturing***	(5) ***Manufacturing***
Value Added Growth	.3250	.3473	.2117	.3530	.3196
	(.1303)**	(.1359)**	(.1370)	(.1281)***	(.1253)**
Labor Compensation per Employee	.1203	.1025	.1433	-.0286	-.0162
(rate of growth)	(.0980)	(.0957)	(0953)	(.0867)	(.0831)
Share of Firms Performing	.0072	-.0471	-.0756	.0040	-.0631
Innovation	(.0365)	(.0513)	(.0521)	(.0470)	(.0622)
Share of Firms Innovating Reducing	-.1096	-.1080	-.1056	-.0141	-.0065
Labor Costs	(.0379)***	(.0506)**	(.0488)**	(.0481)	(.0481)
Inter-Industry Offshoring	-.1134	-.1323		-.1550	
	(.0929)	(.0908)		(.0855)*	
Intra-Industry Offshoring	-.2394	-.2051		-.1494	
	(.0670)***	(.0689)***		(.0612)*	
High-Tech Offshoring			-.0268		-.0658
			(.0726)		(.07712)
Low-Tech Offshoring			-.3555		-.2356
			(.0740)***		(.0633)***
Constant	1.908	3.279	4.627	-5.675	-3.119
	(1.532)	(1.862)*	(1.678)***	(2.865)*	(3.019)
Time Dummy_0003	3.011	3.077	3.051	5.698	5.278
	(1.284)**	(1.287)**	(1.252)**	(1.424)***	(1.431)***
Time Dummy_0307	2.028	2.336	2.461	4.995	4.840
	(1.304)	(1.250)*	(1.221)**	(1.279)***	(1.285)***
Time Dummy_0711	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Country Dummy	No	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	0.12	0.15	0.17	0.28	0.25
N. Obs.	471	471	471	285	289

Weighted Least Squares with Robust Standard Errors in Parenthesis

* significant at the 10% level

** significant at the 5% level

***significant at the 1% level

The Model for Labor Compensation and Wages by Skill-Group

Table 12 presents the results of the regressions on the general variable of labor compensation per employee. Table 9, 9.1 and 9.2 report the coefficient of the regression on wages for each educational-group.

Table 12. Determinants of Labor Compensation per Employee (all Employees).

Dependent Variable: Change in Total Labor Compensation	(1) ***All Industries***	(2) ***All Industries***	(3) ***Manufacturing***	(4) ***Manufacturing***
Hourly Productivity Growth	.3290	.4828	.4234	.5355
	(.0871)***	(.1057)***	(.1368)***	(.1482)***
Total Employment Growth	-.1665	-.1809	-.1844	-.1778
	(.0863)*	(.0848)**	(.0815)**	(.0852)**
Share of Firms Performing Innovation	.0290	.0151	-.0122	.0023
	(.0178)	(.0250)	(.0284)	(.0460)
Share of Firms Innovating Reducing	-.0342	-.0086	.0316	-.0015
Labor Costs	(.0333)	(.0386)	(.0199)	(.0289)
High-Tech Offshoring	-.0766	-.6608	-.1491	-.1394
	(.0466)	(.0446)	(.0644)**	(.0674)**
Low-Tech Offshoring	.1662	.1607	.0183	.0567
	(.0648)**	(.0673)**	(.0924)	(.0924)
Constant	-4.959	-4.967	2.420	.8245
	(1.187)***	(1.866)***	(1.851)	(3.182)
Time Dummy_0003	4.109	3.514	-.7138	-.1757
	(1.011)***	(1.004)***	(.5960)	(.6003)
Time Dummy_0307	5.189	4.793	(omitted)	(omitted)
	(1.040)***	(.9969)***		
Time Dummy_0711	(omitted)	(omitted)	-1.454	-1.282
			(1.218)	(1.230)
Country Dummy	No	Yes	No	Yes
$\mathbf{R^2}$	0.25	0.31	0.11	0.16
N. Obs.	492	492	287	287

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

Confirming expectations, hourly productivity and value added growth are found to have a positive and statistically significant effect for all regressions, while total employment growth and employment growth by professional group show negative and significant coefficients. Looking at the technological variables coefficients, puzzling results emerge. While technology, both in term of process and product innovation strategies, appear to have no effect on labor compensation per employee, wages of educational groups are found to benefit and suffer from innovation by a different degree.

Results suggest that the increase of firms performing product innovation has a negative and significant effect on wages of high and medium-educated workers. Low-educated workers seem not to be affected by this type of technological innovation. If companies implement innovation strategies aiming at launching new products on the market, they must hire new staff and therefore may pay lower wages. Conversely, the increase in the share of firms performing labor saving technology yields positive returns on the average wages of low-skilled workers and to a minor extent on the wage bill of high skilled workers (although only at a very low significance level and in manufacturing industries); we can assume that new process lead to job losses of the low skilled and that the remaining workers are more relevant for production and can be paid higher wages. Medium-skilled workers are negatively affected by this particular form of innovation when country dummy variables are included in the regression. One possible explanation for these findings could be that after implementing cost saving technology, firms pay higher salaries to the remaining labor force. On the contrary, if companies implemented innovation strategies aiming at launching new products on the market they have to invest in new capital and hire more employees resulting in a lower average wage growth.

When considering the results of offshoring, in table 13 it is possible to observe that low-tech offshoring has a positive and statistically significant impact on labor cost per employee while high-tech offshoring has a negative and statistically significant effect but only in manufacturing industries. These results change when considering the cost of labor for different skill-groups. High-tech offshoring has positive and statistically significant coefficients in the model for high-skilled and medium-skilled workers, both in the complete and in the sub-sample of manufacturing industries. Low-tech offshoring has a positive and statistically significant coefficient in the full sample of industries but in the sub-sample of manufacturing industries the low-tech offshoring coefficient is significant only when country dummy are included in the regression.
Results are in line with expectations and in general with the literature that sees offshoring as one of the major factor driving up wage inequality between skill groups (see Bottini et al. 2007 for a detailed review of these studies). The analysis conducted here certainly adds an important element to the puzzle. The technological content of sourced inputs helps to explain

the increasing differential in the economic fortune of workers in industrialized countries. Results tell that high-tech offshoring drive up wages of highly qualified employees while low-tech offshoring drive down wages of less qualified workers.

Table 13. Determinant of Labor Compensation for High-Skilled Workers.

Dependent Variable: Wages Rate of Growth for High-Skilled Workers	(1) ***All Industries***	(2) ***All Industries***	(3) ***Manufacturing***	(4) ***Manufacturing***
Value Added Growth	.8809	.8930	.9790	.9342
	(.0645)***	(.0669)***	(.0924)***	(.0941)***
Managers Rate of Growth	-.9240	-.9279	-.8622	-.8531
	(-.9240)***	(.0293)***	(.0393)***	(.0406)***
Share of Firms Performing Innovation	-.0320	-.0469	-.0725	-.0947
	(.0135)**	(.0163)***	(.0272)***	(.0435)**
Share of Firms Innovating Reducing Labor Costs	.0102	.0159	.0347	.0032
	(.0157)	(.0192)	(.0191)*	(.0327)
High-Tech Offshoring	.0062	.0807	.1088	.1184
	(.0325)*	(.0315)**	(.0454)**	(.0445)***
Low-Tech Offshoring	.0060	.0100	.0023	-.0224
	(.0322)	(.0327)	(.0505)	(.0514)
Constant	3.596	4.290	4.344	7.126
	(.6190)***	(1.348)***	(1.377)***	(1.762)***
Time Dummy_0003	-2.986	-3.040	-2.441	-2.361
	(.5592)***	(.5707)***	(.8275)***	(.8101)***
Time Dummy_0307	(omitted)	(omitted)	(omitted)	(omitted)
Time Dummy_0711	.5181	.4966	.5464	.3925
	(.5311)	(.5525)	(.7755)	(.7859)
Country Dummy	No	Yes	No	Yes
R^2	0.79	0.79	0.71	0.73
N. Obs.	501	501	292	292

Weighted Least Squares with Robust Standard Errors in Parenthesis

* significant at the 10% level

** significant at the 5% level

***significant at the 1% level

Table 14. Determinants of Labor Compensation for Medium-Skilled Workers.

Dependent Variable: Wages Rate of Growth for Medium-Skilled Workers	(1) ***All Industries***	(2) ***All Industries***	(3) ***Manufacturing***	(4) ***Manufacturing***
Value Added Growth	.8273	.8244	.9710	.9317
	(.0902)***	(.0878)***	(.1133)***	(.1154)***
Clerks Rate of Growth	-.7746	-.7499	-.5183	-.4976
	(.0586)***	(.0556)***	(.0565)***	(.0554)***
Share of Firms Performing Innovation	-.0576	-.0351	-.1843	-.1445
	(.0155)***	(.0217)	(.0247)***	(.0426)***
Share of Firms Innovating Reducing Labor Cost	-.0278	-.0603	.0204	-.0174
	(.0208)	(.0340)*	(.0194)	(.0333)
Offshoring High-Tech	.1449	.1485	.1569	.1408
	(.0421)***	(.0420)***	(.0519)***	(.0539)**
Offshoring Low-Tech	.0542	.0778	-.0486	-.0434
	(.0468)	(.0484)	(.0570)	(.0589)
Constant	3.355	3.985	11.02	8.850
	(.7766)***	(1.135)***	(1.580)***	(2.789)***
Time Dummy_0003	-1.286	-1.214	-3.002	-2.436
	(.7875)	(.7734)	(.8550)***	(.9052)***
Time Dummy_0307	(omitted)	(omitted)	-.9720	-.6566
			(.9163)	(.9324)
Time Dummy_0711	-.7984	-.7994	(omitted)	(omitted)
	(.6616)	(.6546)		
Country Dummy	No	Yes	No	Yes
$\mathbf{R^2}$	0.62	0.63	0.58	0.60
N. Obs.	493	493	288	288

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

Table 15. Determinants of Labor Compensation for Low-Skilled Workers.

Dependent Variable: Wages Rate of Growth for Low-Skilled Workers	(1) ***All Industries***	(2) ***All Industries***	(3) ***Manufacturing***	(4) ***Manufacturing***
Value Added Growth	.9034	1.036	1.173	1.222
	(.1095)***	(.1149)***	(.1095)***	(.1084)***
Rate of Change in Manual Workers	-.9959	-.9911	-1.112	-1.109
	(.0404)***	(.0391)***	(.0461)***	(.0473)***
Share of Firms Performing Innovation	-.0240	-.0055	-.0974	-.0159
	(.0182)	(.0265)	(.0201)***	(.0315)
Share of Firms Innovating Reducing Labor Cost	.0474	.0728	.0958	.1139
	(.0189)**	(.0292)**	(.0145)***	(.0272)***
Offshoring High-Tech	-.0356	-.0405	-.0431	-.0464
	(.0399)	(.0409)	(.0396)	(.0402)
Offshoring Low-Tech	-.1347	-.1069	-.1197	-.0366

	(.0419)***	(.0411)***	(.0459)***	(.0456)
Constant	-2.551	-5.755	4.989	-.8905
	(.8130)***	(1.695)***	(1.503)***	(1.690)
Time Dummy_0003	5.811	5.858	.4255	.6051
	(.9226)***	(.9045)***	(.7719)	(.7186)
Time Dummy_0307	(omitted)	(omitted)	-6.436	-6.358
			(.7487)***	(.7471)***
Time Dummy_0711	4.723	5.331	(omitted)	(omitted)
	(.6852)***	(.6970)***		
Country Dummy	No	Yes	No	Yes
R^2	0.81	0.82	0.85	0.87
N. Obs.	477	477	290	290

Weighted Least Squares with Robust Standard Errors in Parenthesis
* significant at the 10% level
** significant at the 5% level
***significant at the 1% level

5. Conclusions

The determinants of employment and wages have been thoroughly investigated. Three major general results confirmed the importance of having paid attention to the heterogeneity of such relationships. First, the distinction proposed between professional groups has shown great differences in the determinants of managers, clerks, craft and manual workers. This confirms the validity of this approach compared to traditional studies that rely only on a superficial subdivision between blue and white collar or high-skilled and low-skilled workers. While offshoring is detrimental to general employment growth, less-qualified workers such as clerks and manual workers may in effect experience the strongest negative contraction in their relative employment levels. Second, the research not only relied on the basic distinction between narrow and broad offshoring but proposed an additional distinction based on the technological level of the foreign industry from which intermediate inputs are sourced. This key distinction has revealed its explanatory power, in particular in the regression on wages by educational group. Third, building on previous work (Bogliacino and Pianta 2011; Cirillo 2014) this work has further confirmed that the distinction between product and product innovation is crucial in determining the effects of technological change on jobs and wages.

Concerning offshoring, inter-industry and intra-industry offshoring as well as high-tech and low-tech offshoring have a negative effect on total employment growth and employment growth by professional group. The subdivision of the sample into manufacturing industries confirms these conclusions. Coefficients show the same sign and a very similar order of magnitude. The division of employment in four professional groups instead adds important information to the conclusions. Offshoring has an overall neutral effect on managers and on craft workers. Clerks, and to a much bigger extent manual workers, are heavily hit by international fragmentation of production with low-tech offshoring causing the largest drop in the rate of growth for this professional group. Concerning clerks, it is possible to conclude that offshoring involves highly routinized office functions like accounting, customer service and programming that thanks to improved telecommunication technology can be easily carried out from remote locations. Concerning manual workers, offshoring certainly involves relocation towards developing and emerging economies of routinized production functions where labor cost is much lower compared to the five European countries analyzed here. The substitution away of low value-added tasks replace home with foreign manual workers.

Results of the regressions on wages by educational groups are very much in line with the findings above confirming the heterogeneity of the relationships analyzed. High-tech offshoring is found to have a negative effect on labor compensation per employee while low-tech offshoring a positive effect. This means that the offshoring of high-tech inputs replace domestic production, placing domestic workers in western countries in direct competition with foreign workers. On the contrary, offshoring of low-tech goods may increase domestic productivity and consequently the wage premium for workers. Since low value added tasks are carried out by external partners, firms can concentrate internal resources on more profitable operations with higher value added.

The picture is reversed in the analysis of labor compensation by skill-group. Here, imports of intermediate input from foreign high-tech industries have positive effects on the wages rate of growth for high and medium-skilled workers while low-tech offshoring have a negative effect on wages of low-skilled workers. It is likely that while imports of high-tech intermediate goods increase productivity and hence wages of more advanced skill-groups, low-tech offshoring exposes less qualified workers to international competition from countries where the cost of unskilled labor is comparably lower. In this sense, further research is required to identify the geographical origin of imported intermediate inputs.

To conclude, it is important to emphasize the relevance and the validity of the approach that suggested differentiating employment and wages in professional or educational categories.

This study confirmed the polarization of employment in Europe towards high-skilled professions and the general downsizing of local manufacturing industry, particularly after the recent economic crisis. Furthermore, the key distinction in the technological content of imported intermediate inputs revealed its explanatory power that opens up possibilities for further research.

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APPENDIX

Table 1. NACE Rev.1 Sectors

	SECTORS	Nace Sectors	Pavitt-Class
Nr.	**MANUFACTURING**		
1	FOOD PRODUCTS, BEVERAGES AND TOBACCO	15 - 16	SD
2	TEXTILES	17	SD
3	WEARING APPAREL, DRESSING AND DYEING	18	SD
4	LEATHER, LEATHER PRODUCTS AND FOOTWEAR	19	SD
5	WOOD AND PRODUCTS OF WOOD AND CORK	20	SD
6	PULP, PAPER AND PAPER PRODUCTS	21	SI
7	PRINTING AND PUBLISHING	22	SI
8	COKE, REFINED PETROLEUM PRODUCTS AND NUCLEAR FUEL	23	SI
9	CHEMICAL AND CHEMICAL PRODUCTS	24	SB
10	RUBBER AND PLASTIC PRODUCTS	25	SI
11	OTHER NON-METALLIC MINERAL PRODUCS	26	SI
12	BASIC METALS	27	SI
13	FABRICATED METAL PRODUCTS (EXCEPT MACHINERY AND EQUIPMENT)	28	SD
14	MACHINERY AND EQUIPMENT, NEC	29	SS
15	OFFICE, ACCOUNTING AND COMPUTING MACHINERY	30	SB
16	ELECTRICAL MACHINERY AND APPARATUS, NEC	31	SS
17	RADIO, TELEVISION AND COMMUNICATION EQUIPMENT	32	SB
18	MEDICAL PRECISION AND OPTICAL INSTRUMENTS	33	SB
19	MOTOR VEHICLES, TRAILERS AND SEMITRAILERS	34	SI
20	OTHER TRANSPORT EQUIPMENT	35	SS
21	MANUFACTURING NEC AND RECYCLING	36	SD
Nr.	**SERVICES**		
22	SALE, MAINTENANCE AND REPAIR OF MOTOR VEHICLES; RETAIL SALE OF FUEL	50	SD
23	WHOLESALE, TRADE & COMMISSION EXCLUDED MOTOR VEHICLES	51	SD
24	RETAIL TRADE, EXCL. MOTOR VEHICLES; REPAIR OF HOUSEHOLD GOODS	52	SD
25	HOTELS AND RESTAURANTS	55	SD
26	LAND TRANSPORT	60	SD
27	SEA TRANSPORT	61	SD
28	AIR TRANSPORT	62	SD
29	SUPPORTING AND AUXILIARY TRANSPORT ACTIVITY	63	SD
30	POST AND TELECOMMUNICATION	64	SB
31	FINANCIAL INTERMEDIARIES (EXCEPT INSURANCE AND PENSION FUND)	65	SI
32	INSURANCE AND PENSION FUNDS (EXCEPT COMPULSORY SOCIAL SECURITY)	66	SI
33	ACTIVITIES RELATED TO FINANCIAL INTERMEDIARIES	67	SI
34	REAL ESTATE ACTIVITIES	70	SS
35	RENTING OF MACHINERIES AND EQUIPMENT	71	SS
36	COMPUTER AND RELATED ACTIVITIES	72	SB
37	RESEARCH AND DEVELOPMENT	73	SB
38	OTHER BUSINESS ACTIVITIES	74	SS

Pavitt Classes: SB Science based, SS Specialized Suppliers, SI Scale Intensive, SD Supplier Dominated

Table 2. Variables Correlation Matrix (with * at the 5% Significance Level).

	Value Added	Hourly Prod.	Labor Cost	Innovation	Cost Comp.	V_Tot Wo.	V_Managers	V_Clerks	V_Craft W.	V_Manu_W.	Wage_High	Wage_Med.	Wage_Low	Off_Diff	Off_Narr	Off_HT	Off_LT
Value Added	1																
Hourly Prod.	0.3972*	1															
Labor Cost	-0.0307	0.2770*	1														
Innovation	0.0867	0.2056*	0.0361	1													
Cost Comp.	0.0254	0.1965*	0.1078*	0.3387*	1												
V_Tot Wo.	0.3026*	-0.1672*	-0.1550*	0.006	-0.1454*	1											
V_Managers	0.1603*	-0.0859*	-0.0775	-0.0974*	-0.1165*	0.6169*	1										
V_Clerks	0.0802	-0.1217*	-0.1030*	-0.0252	-0.0867*	0.5460*	0.2212*	1									
V_Craft W.	0.1110*	-0.1000*	-0.1230*	0.0167	-0.0866	0.4890*	0.1630*	0.2927*	1								
V_Manu_W.	0.1487*	-0.0081	0.082	-0.0966*	-0.1347*	0.4888*	0.2509*	0.1841*	0.1855*	1							
Wage_High	0.2774*	0.1426*	0.1011*	0.0326	0.074	-0.3810*	-0.7161*	-0.2134*	-0.0832	-0.1442*	1						
Wage_Med.	0.3091*	0.1851*	0.1526*	-0.0497	0.0576	-0.3079*	-0.011	-0.6190*	-0.4607*	-0.0286	0.3374*	1					
Wage_Low	0.1395*	-0.0248	-0.0943*	0.0427	0.1585*	-0.3043*	-0.1557*	-0.0879*	-0.1143*	-0.8177*	0.2402*	0.1456*	1				
Off_Diff	-0.1052*	0.1102*	0.0238	0.0951*	0.1108*	-0.2013*	-0.0815	-0.0526	-0.0689	-0.1070*	0.0495	0.0714	0.0666	1			
Off_Narr	-0.1296*	0.2202*	0.1404*	0.3849*	0.3476*	-0.2865*	-0.1432*	-0.1819*	-0.1321*	-0.1879*	0.0859*	0.1311*	0.1067*	0.1441*	1		
Off_HT	0.0409	0.2337*	-0.0195	0.3901*	0.2990*	-0.1434*	-0.1135*	-0.0951*	-0.0637	-0.1045*	0.1271*	0.1163*	0.0803	0.5344*	0.6269*	1	
Off_LT	-0.2978*	0.0697	0.2199*	0.0492	0.1309*	-0.3385*	-0.0990*	-0.1424*	-0.1446*	-0.1851*	-0.0117	0.0749	0.0818	0.3450*	0.5452*	-0.0421	1

Source: Own Elaboration.