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The dynamics of profits and wages: technology, offshoring and demand

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Abstract

This article explores the impact of innovation, offshoring and demand on profits and wage dynamics. The growing relevance of functional distribution in terms of explaining personal distribution underscores the importance of our results for understanding recent increases in inequality. The empirical analysis performed herein involves a panel of 38 manufacturing and service sectors over four time periods (1995 to 2010) across five European countries (Germany, France, Italy, Spain and United Kingdom). Our identification strategy relies on instrumental variables and recently proposed heteroskedasticity-based instruments (Lewbel, 2012). Additionally, we perform sensitivity analysis to account for omitted variables bias, following the recent theoretical results of Oster (2015). The main results of our study can be summed up in three points. First, it highlights the contrasting effects of R&D and offshoring as wage determinants—the former exerts a positive effect while the latter exert a negative effect. Second, it shows that external demand is a key variable driving profits growth. Third. it provides evidence of noteworthy results stemming from the categorization of workers according to skill level, such as: high-skilled workers are favored by both innovation and offshoring, offshoring exerts downward pressure primarily on low-skilled wages (not on medium-skilled wages as predicted by SBTC) and profits are positively correlated with high-skill wages, negatively correlated with medium-skill wages and not correlated with low-skill wages.

Keywords: *rent; surplus; distribution; inequality; skills; offshoring; R&D*
JEL Classification: *O33, F15, J31*

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1. Introduction

1.1 Background

Although *personal* (i.e. across households) distribution of income is mainly explained by earnings distribution, the rise in inequality witnessed from the 1980s to today has been increasingly affected by *functional* (i.e. across factors of production) distribution of income (OECD, 2008; 2011; Bogliacino and Maestri, 2014; Piketty, 2014).

In this article, we identify the impact of demand, innovation and the international fragmentation of production (offshoring) on capital and labour remuneration. Within our theoretical framework, wage setting is affected by total employment, capital installed and total production, like we see in a standard labour demand framework; however, our framework is enhanced by the inclusion of the international organization of production and technical change. Once bargained, wage represents a constraint on capital, and the market realization of profits depends upon various sources of demand, as in a standard Kaleckian and post-Keynesian framework (Kalecki, 1939; Arestis, 1996, although classical arguments *à la* Ricardo, 1815 and Marx, 1867 should not be disregarded).

Our approach departs from existing explanations of the change of inequality over the last three decades. The most common hypotheses have focused almost exclusively on the labour market, thereby suggesting that either trade or technical change have driven the growing earnings dispersion. Trade-related explanations stress the role played by China or other unskilled labour-abundant countries, whose entrance into the global economy affects the skill premium in developed countries through comparative advantages. For their part, technical change arguments propose a skilled bias hypothesis (SBTC hereafter), that is, they propose complementarity between technology and skills based on new innovations.[1]

On the contrary, we claim here that the conflict between labour and capital must be taken into account. Firstly, since capital income is more unequally distributed than labor, a reduction of the labor share increases total inequality, and the increase in capital share has been remarkable in most OECD countries (Arpaia et al., 2009; Checchi and Garcia-Penalosa, 2010; Jorgenson and Timmer, 2011; Stockhammer; 2013; Schlenker and Schmid, 2013; Van der Hoeven, 2014; ILO, 2015). The impact of capital share on household income distribution may actually be underestimated for two reasons: on one hand, most profits go to the top one percent, and standard measures, such as the Gini, are not very sensitive to changes in the tails (Atkinson et al. 2011; Bogliacino and Maestri, 2014); on the other, performance-related payments to

[1] The evidence suggests that the skill premium increased in both developed and developing countries (Acemoglu, 2002; Acemoglu and Autor, 2011). Moreover, most of inequality increase has been within sector, which contradicts the hypothesis that holds comparative advantages (reflected in changes between sectors) are the main driver (Bogliacino and Maestri, 2014). As it so happens, this was taken to uphold the view that technical change should be considered primarily responsible for the increase in inequality. Empirical estimates simultaneously accounting for trade and SBTC confirms the finding (Morrison Paul and Siegel, 2001).

managers (i.e. the salary of the so-called *working rich*) are not considered profits in many countries, though they should be (Stiglitz, 2012).

Secondly, profits are the main driver of accumulation in a capitalist economy over the long run. As a result, labour market decisions and choice of technique are obviously related to both capital and labour. As Howell (1999) and Atkinson (1999) contend, distributive arrangements are possible options of a range determined by demand and supply, social norms and policy constraints, in which rents are continuously created and shared.

One of this paper's original insights lies in its isolation of the effect of technical change and offshoring on the bargaining between capital and labour and between capital and different groups of workers. Another important contribution is the estimation of the impact of various sources of demand on profits growth.

1.2 Relation to Existing Literature

Our article is directly related to structural analyses that use industry-level data. Every unit of analysis (whether micro, meso or macro) has its own pros and cons, e.g. firm-level data systematically account for heterogeneity, yet usually fail to meet external validity. In a series of recent papers (Lucchese and Pianta, 2012; Bogliacino and Pianta, 2013a; 2013b; Guarascio et al., 2014 and 2015), the methodological choice of sectoral data is premised on two principal arguments: i) demand is not a constraint at firm level, where business stealing allows firms to grow at the expense of their competitors, but it is downward sloping at industry level; ii) technological trajectories are only partly captured at the micro level using proxies of technical change, while industry level variables internalize, to some extent, the knowledge base and spillovers (i.e. the network of actors and flows that constitutes a sectoral system of innovation, Dosi, 1988; Malerba, 2004).

Furthermore, our article directly contributes to the literature on determinants of the functional distribution of income (e.g. Pianta and Tancioni, 2008; Basu and Vasudevan, 2013). Pianta and Tancioni (2008) have previously attempted to analyze the effect of technical change by distinguishing product and process innovation. They have shown that profits are driven by the 'Schumpeterian' effects of new products. Wages, however, tend to be pushed upwards by new products in highly innovative sectors, whereas process innovation drives them downwards in low-tech industries. In the post-Keynesian literature, the emphasis has, instead, shifted to the role of demand. Stockhammer (2013), for example, has analyzed the declining wage share in OECD countries, claiming that the most meaningful determinants are technological change, offshoring, the increasing importance of financial activities in the economy, globalisation and reforms aimed at reducing the size and scale of the welfare state. Admittedly within a slightly different framework, Palma (2009) has argued that what got the four capital-share increasing engines going (and increased the income of the top 1%) is a fundamental shift of risk from capital to labour, which, in turn, paves the way for a new politico-economic equilibrium.[2] An opposing view on the decline in labour share attributes the causal role to the decline in the price of capital goods (Karabarbounis and Neiman, 2014).

We add to the literature on innovation's effect on wages. In modern economic theory, the idea that technical change is not neutral can be likely ascribed to Hicks (1932)—although the labor-saving bias in favor of machines was clearly present in Marx and Ricardo—suggesting that labor-saving innovation is driven by falling prices of capital. Hicks's study has engendered a notable discussion of the possibility of an *a priori* discrimination of technology bias (Salter, 1960) or the technical conditions in terms of elasticity of substitution among factors necessary to determine an induced bias (Fellner, 1961; Kennedy, 1964; Samuelson, 1965; Von Weiszacker, 1966; Drandrakis and Phelps, 1966; more recently, Zamparelli, 2011).

Despite originally taking place in the 1960s, this theoretical discussion was revived in the 1990s; this time, it formed part of the debate over the massive introduction of ICT technologies and their effect on the dynamics of wages (Berman et al., 1994). An expansive theoretical literature has emerged in response to this debate; essentially, the conclusion has been that new technologies complement skills (Acemoglu, 2002; Acemoglu and Autor, 2011). The prediction proposed by SBTC can be regarded as ambiguous, unless we specify whether bias is endogenous or not. According to Acemoglu and Autor (2011), bias ought to be made endogenous to the variations of the supply of skills, for these variations alter the patterns of incentives for those inventing task-related machinery.[3] Nevertheless, Bogliacino and Lucchese (2015) have used the German reunification shock over West Germany as a natural experiment in the variation of the supply of skills, for which they found no evidence of induced SBTC.

Another shortcoming of SBTC is brought to the forefront by OECD (2011) and Bogliacino and Maestri (2014): institutional reforms in the labour markets appear to be responsible for most of the change in wage inequality. As we argue here, the conceptual problem related to SBTC is that technology *per se* creates rents. The way those rents are shared should depend on bargaining between labour and capital (with institutional factors certainly playing a role). We build on work done by Van Reenen (1996) and Bogliacino (2014) to propose a simple model of sharing innovation-related rents.

Finally, our work contributes to the literature on offshoring's impact on wages. High-skilled wages may benefit from the offshoring of the relatively labour-intensive parts of the production

[2] The role of finance in the economy is contested in the heterodox literature, but the direction of causation is not clear. Lysandrou (2011) and Perugini et al. (2015) suggest that increasing inequality led to the increased financial instability on account of increasing demand for securitization and engineering of new low-risk assets. Statistically, financial sector wages represent a significant portion of the increase in *personal* income inequality, according to Allison et al. (2014).

[3] In other words, if a firm is free to invent machinery for a skill-intensive task or an unskilled intensive one, the total supply of skills will obviously affect the market for its invention, in line with classical demand- pull arguments (Bogliacino and Lucchese, 2014; Acemoglu, 2002; Schmookler, 1966).

process because of two mechanisms: (a) via a standard comparative advantage effect; (b) via an "organizational innovation," that is, the participation in the high-tech and highly-valued Global Value Chain (GVCs). However, low- and medium-skilled wages are subject to potentially negative effects; namely, the threat of delocalizing production can reduce bargaining power.

The empirical literature, which has recently undergone substantial expansion, has not arrived at a consensus regarding offshoring's impact on wages. While there are articles suggesting that it may cause large employment losses among low-skilled workers and increase the wage differential (Feenstra and Gordon, 1997; Feenstra and Hanson, 1996 and 1999; Amiti and Wei, 2004; Munch, 2010; Sheng and Yang, 2012),[4] Antràs et al. (2006) have argued that the effect of offshoring on wages is negligible. Furthermore, these authors claim that the only impact, albeit moderate, is a positive one insofar as high-skilled workers located in the offshoring countries are concerned (see also Falk and Koebel, 2002 for Germany). Using a multi-country model of international trade, Burstein and Vogel (2012) have detected a positive relationship between offshoring and high-skilled wages and no correlation between offshoring and countries' skill endowments. Yet, these results have not been confirmed by Hummels et al. (2014), who identified negative effects stemming from the offshoring decisions of Danish firms on wages of unskilled workers. Costinot et al. (2013) has concluded that the impact of offshoring on wages is strongly heterogeneous due to the different skill compositions of industrial sectors (similar notions have been proposed by Fosse and Maitra, 2012; Milberg and Winkler, 2010 and 2013; Timmer et al, 2013 and Hummels et al., 2014).

Another research track (Slaughter, 2000; Geishecker and Görg, 2008; Mion and Zhu, 2013 for Belgium; Autor et al., 2013 for the US) makes the case for offshoring's negative effect on the employment level and wage share of medium-skilled workers in developed economies. In this vein, Foster et al. (2012) have analyzed the impact of offshoring on labour demand elasticity for a group of 40 countries over the period 1995-2009; they have found a neutral effect of offshoring on aggregate employment, although the effect was negative for low- and medium-educated workers. Additionally, combining effects on labour and wages, Harrison et al. (2009) have demonstrated the differentiated impact of international trade and offshoring on US wages and employment across selected occupations.

Regarding offshoring and profits, Görg and Hanley (2011) have estimated the impact of service offshoring on firms' profits and innovative behavior. Working with g a sample of 1,929 Irish plants, the authors have observed the positive effects of service offshoring on firm's

[4] Carluccio et al. (2015b) claim that the wage premium depends upon the participation of international trade and collective bargaining. Workers in high-skilled occupations complement overseas production, while workers in low-skilled occupations serve as substitutes. This effect is also related to collective bargaining, and, surprisingly, wage gains to sign firm-level agreements accrue to all workers regardless of trade intensity with a 10% wage gap when compared to industry agreements. Carluccio et al (2015a) determined that skill upgrading due to offshoring occurs within—and not among—industries.

profitability and on firm's innovativeness, and Hijzen et al. (2010) have obtained similar results based on a panel of Japanese firms.

1.3 Main Results

Our empirical strategy relies on standard instrumental variables and the recently proposed heteroskedasticity-based instrumental variables approach (Lewbel, 2012). Identification is achieved with the use of regressors not correlated with the product of heteroskedastic errors. With this approach, *atheoretical* instruments can be generated, and proper statistical tests can be provided for both the heteroskedasticity requirement and the over-identifying restrictions.

We apply our framework to industry-level data for five European countries (Germany, France, Italy, Spain, and United Kingdom) over the period 1995-2010. Our database merges data from the Community Innovation Survey, OECD STAN and WIOD, thus allowing for the measurement of different sources of demand, technology and offshoring.

We address the issue of omitted variables by means of recent methods of sensitivity analysis (Oster, 2015). Given certain assumptions regarding the relative role of observable and unobservable variables, this technique allows us to estimate the robustness of the computed effect of problems arising from omitted variables.

Our main results are as follows. We find a positive and negative effect exerted by R&D and offshoring, respectively. Exports and, to a lesser extent, internal demand are key variables for the realization of profits. When we look at the heterogeneity of effects, specifically with regard to the structure of workers' skills structure, three main stylised facts must be broached. Firstly, R&D-driven innovation affects high- and medium-skilled wages but not low-skilled ones. Secondly, high-skilled wages have experienced more growth in "offshoring intensive" industries, whereas medium- and low-skilled wages tend to decrease in the same sectors. Indeed, this finding supports the hypothesis of offshoring's 'threat effect' on low-skilled workers' bargaining power but not that of medium-skills workers, which clashes with the main prediction made in SBTC literature (Acemoglu and Autor, 2011). Thirdly, the basic macro conflict between capital and labour does not preclude a difference in bargaining across skills: high-skilled wages tend to move as profits do, while medium- and low-skills tend to move in the opposite direction with respect to profits.

The article proceeds as follows: Section 2 presents the theoretical framework; Section 3 describes the database and the methodology; Section 4 illustrates the results; and Section 5 concludes.

2. Theoretical Framework

Our structural model is founded on two primary building blocks. In a nutshell, our approach is based on the following sequential timing: wages are bargained before entering into production and take into account the constraints dictated by total employment, output decisions and available or expected rents (related innovation and organization of production). Profits are realized afterwards, depending, of course, on the surplus residual (in a Ricardian sense, i.e. after paying wages) and on demand level.

On the wage determination side, we are guided by Van Reenen's hypothesis (1996) regarding 'innovation rents' captured by workers (in a similar vein, see Dunne and Schmitz, 1995). Van Reenen's hypothesis is predicated on the efficiency wage theory (Akerloff and Yellen, 1990). According to this theory, a causal relationship can be traced between wage level and worker's on-the-job productivity. Employers are willing to pay wages above the market-clearing level in order to spur productivity growth; basically, worker productivity depends on wages received, implying higher wages is akin to more incentive for the worker to be productive. Furthermore, according to Shapiro and Stiglitz's model (1984), a wage increase is shown to decrease a worker's incentive to shirk. In other words, a wage increase boosts worker productivity and lowers direct monitoring expenses.[5]

Innovative rents are defined in Schumpeterian terms, and they should be derived from the temporary monopoly associated with a new product (Schumpeter, 1942). Van Reenen (1996) identifies three fundamental reasons why workers have legitimate access to portions of innovation rents: i) the time lag between input, R&D activities and output of innovation; ii) the difference in time horizon between workers and shareholders, which is shorter for the former due to the diffusion of temporary contracts; iii) the elements of randomness in the nature of innovation.

Our theoretical specification of wage determinants follows the extension of the innovation rent hypothesis as formulated by Bogliacino (2014). We adapt this model of wage determination—originally meant to study the relation between technical change and firm's labour demand—to identify the simultaneous role and interplay of technical change and offshoring in shaping wage dynamics.

To model profits, we combine our wage equation with a Kaleckian profit. As a result, the profits equation accounts for the role of demand as well as the effect of social conflict. We determine that the impact of wage variations on profits is indirectly shaped by the contrasting effect, and interaction, of technical change and production offshoring.

[5] In this sense, the wage explanation put forth by the "shirking model" predicts wage differentials depend on the amount of monitoring costs between different firms and industries. Higher monitoring costs lead to higher wages. Similarly, wage differentials have been shown to be related to firm size (where monitoring costs are higher) by various researchers (Davis and Haltiwanger, 1991; Main and Reilly, 1993; Brunello and Colussi, 1998; Arai, 2003; Lallemand et al., 2005; more recently Bottazzi and Grazzi, 2010). We should stress that the efficiency wage literature deals with the "residual" labour productivity, which does not depend on capital equipment or technology. *Ceteris paribus* labour productivity may depend on (greater) worker effort and incentives on the jobs by the employers.

In the second part of this paper, we turn our attention to the heterogeneous impact after accounting for the classification of workers by skill.

2.1 The Wage Equation

The wage equation is a standard log-linear specification augmented with a term for surplus sharing. The fact that technology and organization of production affect the creation and distribution of rents means we can, in principle, use a non-linear equation:

$$\log(W_{it}) = \alpha_0 + \alpha_1 log(L_{it}) + \alpha_2 log(Y_{it}) + \alpha_3 \log\left(\Phi(\log(OFF_{it}), \log(R\&D_{it})\right) + \epsilon_{it} \qquad (1)$$

where subscript i and t indicate the industry-country couple and the observation time, respectively; w stands for wage, L for employment, Y for total output and $R\&D$ and OFF represent R&D and offshoring, respectively.[6]

The Φ function non-linearly captures the effects of technology and organization of production.

This wage equation can be viewed as an extension of Bogliacino's (2014) specification, for the author explains the relationship between technical change and labour demand at the firm level by considering "innovation rents." Using firm's R&D expenditure as a proxy for innovation, Bogliacino (2014) suggests a non-linear relationship between technical change and labour demand. Such nonlinearities are determined by a scale effect—linked to the decreasing returns to scale of R&D investments owing to fixed factors—and a size effect—linked to larger firm's ability to exploit greater benefits from research activities. As previously mentioned in the introduction, the presence of such non-linearity may be better captured at the industry level than at the micro level because of spillover effects.

In the present investigation, the theoretical framework is broadened to account for the organizational change associated with offshoring. Similarly, due to organizational and product innovation (related to offshoring and R&D, respectively), rents may accrue, and these rents are bargained for in the labour market.[7]

To identify the effects of R&D and offshoring, we must expand the Φ function in (1) with a Taylor approximation. If we take a log formulation, we get (2):

$$log\Phi(z, y) =$$

$$log\Phi(0,0) + \frac{\Phi_1(0,0)}{\Phi(0,0)}x + \frac{\Phi_2(0,0)}{\Phi(0,0)}y + \left(-\Phi^{-2}(0,0)\Phi_1^2(0,0) + \Phi^{-1}(0,0)\Phi_{11}(0,0)\right)x^2 +$$

[6] Furthermore, (1) can be formally derived from the first order conditions with a Constant Elasticity of Substitution (CES) production function (Chennels and Van Reenen, 1999).

[7] Bogliacino (2014) shows that at firm level it is possible to obtain this formulation as a structural equation for labour demand at in the context of a patent race model *à la* Dasgupta and Stiglitz (1980). We broadened this framework to capture the effects of offshoring.

$$2\left(-\Phi^{-2}(0,0)\Phi_1(0,0)\Phi_2(0,0)+\Phi^{-1}(0,0)\Phi_{12}(0,0)\right)xy+$$
$$\left(-\Phi^{-2}(0,0)\Phi_2^2(0,0)+\Phi^{-1}(0,0)\Phi_{22}(0,0)\right)y^2+o\|(x,y)\|^2 \tag{2}$$

where z and y are R&D and Offshoring variables in log terms, respectively. Now, we can express our specification of the wage at the industry level:

$$\log(W_{it})=\alpha_1 log(L_{it})+\alpha_2 log(Y_{it})+\alpha_3 log(R\&D_{it})+\ \alpha_4\log(OFF_{it})+\alpha_5 log^2(R\&D_{it})+$$
$$\alpha_6\log(R\&D_{it}*OFF_{it})+\ \alpha_7 log^2(OFF_{it})\ +\ u_i+\ e_{it} \tag{3}$$

Differentiating (3) to get rid of the fixed effects u_i,[8] we finally obtain our empirical specification of the wage equation (4):

$$\Delta\log(W_{it})=\alpha_1\Delta log(L_{it-1})+\alpha_2\Delta log(Y_{it-1})+\alpha_3\Delta log(R\&D_{it-1})+\ \alpha_4\Delta\log(OFF_{it-1})+$$
$$\alpha_5\Delta log^2(R\&D_{it-1})+\alpha_6\Delta\log(R\&D_{it-1}*OFF_{it-1})\ +\alpha_7\Delta log^2(OFF_{it}-1)+\ \Delta e_{it} \tag{4}$$

Per equation (4), wages are driven by: the level of economic activity at the sectoral level (which is determined by the firm); innovation; and, offshoring activities, which may interact and have non-linear effects.[9]

All explanatory variables used here are lagged. Theoretically, we operate from the assumption that the effects of market dynamics (or proxied by the change in output and employment), innovation (proxied by R&D efforts) and investments (proxied by expenditure on new machinery) or are observable after a one period lag (analogous specifications can be found in Bogliacino and Pianta, 2013a; 2013b and Guarascio et al, 2015). Empirically, the inclusion of lagged variables—not ignoring that variables are already expressed as four-year lags—helps eliminate the risk of simultaneity-related endogeneity (see 3.3 for more on this point).

We expect firms' R&D efforts to exert a positive effect on wage dynamics, as propounded by the "innovation rent" hypothesis (Van Reenen, 1996). If this hypothesis holds true, offshoring variables will negatively affect wages by means of offshoring's weakening effect on worker's bargaining power. The interaction term between R&D and offshoring activities may have varying sign and significance due to the preponderance of one of the two effects.

Moreover, the magnitude and direction of innovation and offshoring with regard to wages may also differ according to workers' skill categories. We expect high-skilled workers to be more apt

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[8] We should mention that fixed effects also capture country-level institutional variables, which clearly affect the labour market.

[9] In line with Kramarz (2008), we hypothesize that offshoring can affect wages by altering the firm's threat point and, thus, changing the overall rent shared by firms and workers. In other words, firms willing to reduce union strength use offshoring as an instrument to discipline workers.

to capture higher shares of "innovation rents" relative to medium- and low-skilled ones. In the case of offshoring, we expect a similar outcome: a more conspicuous negative effect on wages for low- and medium-skilled workers.

2.2 The Profits Equation

As we had anticipated, the profits equation is sequential with respect to wages, for actual profits depend on potential profits (surplus) and demand. In our formulation, we expand on Kalecki (1939), using input-output matrices to disaggregate different source of demand.
Profits are the realized surplus after sharing portions of the rents with the workers.

$$\Pi = pq - cq - sq \tag{5}$$

Where p is the price, c is the unit cost (in a classical sense, e.g. reproduction costs) and the last term is the rent shared with the workers (s if the unit rent accruing to workers). Based on (5), we can define the markup (m) as the difference between price and unit cost; including logarithms, we have the expression:

$$\log\ (\Pi) = \log\ (m - s) + \log\ (q) \tag{6}$$

To identify the first term, we need a bargaining conflict variable and a markup variable. Although we have technology and offshoring, both are related to ex-ante investment and present risk, which is why we have included them in the wage equation. Consequently, we use investment as a measure of embodied technical change, e.g. successful innovation (Dosi, 1988). It is important to note that for the markup we also control for average firm size to ensure that this variable proxies the market concentration of industries. As a measure of bargaining conflict, we utilize the estimated rate of change of wages given by equation (4). To capture the second term in (6), we turn to the input-output structure, identifying the different sources of demand, i.e. both internal and external.
Therefore, we can build off of (6) to establish our simple empirical specification of industry profits:

$$\log(P_{it}) = \alpha_0 + \alpha_1 \log(SIZE_{it}) + \alpha_2 \log(I_{it}) + \alpha_3 \log(C_{it}) + \alpha_4 \log(EXP_{it}) - \alpha_5 log(W_{it}) + u_i + \varepsilon_{it} \tag{7}$$

where subscripts i and t indicate the industry-country couple and the time of the observation, respectively; w stands for wage, EXP for export, C for consumption demand and I for investment.

Taking the first difference of (8) to remove the fixed effects u_i, we get:

$$\Delta \log(P_{it}) = \alpha_1 \Delta \log(SIZE_{it}) + \alpha_2 \Delta log(I_{it}) + \alpha_3 \Delta log(C_{it}) + \alpha_4 \Delta \log(EXP_{it}) - \alpha_5 \Delta \log(W_{it}) + \varepsilon_{it} \qquad (8)$$

where, the wage is the estimated from (4). The following effects are expected: the presence of large firms—signaling a relatively low degree of competition within the sector—is positively correlated with variations in profits; expenditure on new machinery and equipment—i.e. embodied technological change—and demand positively affect variations in profits; wages, on the contrary, negatively impact profits and, in so doing, capture bargaining conflict.

3. Data and Methodology

3.1. The SID Database

For this paper, we use the Sectoral Innovation Database (SID) developed at the University of Urbino (Pianta et al., 2011). The SID is the result of combining different data sources with the sector as the unit of analysis. For innovation variables, such as R&D expenditure, average firm size and expenditure on new machinery and equipment, data are drawn from four European Community Innovation Surveys—CIS 2 (1994-1996), CIS 3 (1998-2000), CIS 4 (2002-2004) and CIS 6 (2008-2010)—and subsequently matched to industry-level data from the WIOD Nace Rev. 1 database. In order to establish the requisite condition for comparability, innovation variables taken from CIS6 have been converted into Nace Rev.1 using the conversion matrix found in Perani and Cirillo (2015).

For production and demand variables, that is, wages, profits, demand and total employees, we use data from the World Input Output Database (WIOD). Input-Output tables are employed to connect domestic and imported inputs and industries, thus helping disentangle the production structure (Yamano and Ahmad, 2006 and Timmer et al., 2013). All data have been converted into euros and constant prices. Data are available for the two-digit NACE classification for 20 manufacturing and 17 service sectors; all data refer to the total activities of industries.[10]

The country coverage of the database includes five major European countries (Germany, France, Italy, Spain, and United Kingdom) that represent the majority of the European economy (71% of the entire EU28's GDP). The selection of countries and sectors has been made with an eye toward avoiding limitations in data access (on account of the low number of firms in a given

[10] In line with the precedent established by empirical literature on the impact of offshoring, we excluded the (Nace Rev.1) sector 23 (mineral oil refining, coke & nuclear fuel). Previous analyses performed using WIOD and SID data showed that results were quite sensitive to the inclusion of this particular sector. The sector stands out in many respects; for instance, it has a very high degree of vertical specialisation, high energy intensity, extremely high labour productivities, excessive capital coefficients, etc. To recapitulate, this industry is excluded from our results in order to avoid distorted results (Foster et al., 2012; Landesmann and Leitner, 2015).

sector for a given country or on account of the policies on data released by various National Statistical Institutes).

As for the panel's time structure, economic and demand variables are calculated for the periods 1996-2000, 2000-2003, 2003-2007 and 2007-2010. Innovation variables are taken from innovation survey (data gathered in waves): the first wave (CIS II) spans 1994-1996 and aligns with the first period of economic variables; the second wave (CIS III) spans 1998-2000 and aligns with the second period of economic variables; the third wave (CIS IV) spans 2002-2004 and aligns with the third period of economic variables; the last wave (CIS VI) spans 2006-2008 and aligns with the fourth period of economic variables. See Table 1 for the variables used.

Table 1. List of Variables

Variable	Unit	Source
In-house R&D exp. per employee	Thousands euros/empl	SID – (CIS Var.)
New machinery exp. per employee	Thousands euros/empl	SID – (CIS Var.)
Average firm size	Number of employee	SID – (CIS Var.)
Rate of gr. of Exports	Annual rate of growth	SID - (WIOD I-O Var.)
Rate of gr. of Intermediate Demand	Annual rate of growth	SID - (WIOD I-O Var.)
Rate of gr. of Final Demand	Annual rate of growth	SID - (WIOD I-O Var.)
Rate of gr. of Offshoring (F&H Nar.)	Simple difference	SID - (WIOD I-O Var.)
Rate of gr. of Wages	Annual rate of growth	SID - (WIOD I-O Var.)
Rate of gr. of Profits	Annual rate of growth	SID - (WIOD I-O Var.)

Source: Sectoral Innovation Database (Pianta et al., 2011). Note: Rate of growth are compound annual rate of growth computed over four and three year periods (1996-2000; 2000-2003; 2003-2007; 2007-2010). In the estimations, wages variation is considered both per capita and per worked hour. Wages are computed for the industries' aggregate and divided by skill (High, Medium and Low skill) according to the ISCED classification.

Economic variables are deflated using the sectoral Value Added deflator from WIOD (base year 2000), corrected for PPP (using the index provided by Stapel et al. 2004). To determine the performance variable, we compute the compound annual growth rate that approximates the difference in log; to determine innovation variables, we use expenditure per employee (the flow) as a proxy for the change in the stock. Wage variables are expressed as hourly wage. We rely on a narrow definition of international outsourcing that considers only imported intermediates in a given industry from the same industry (corresponding to diagonal terms of the import-use matrix). Feenstra and Hanson (1996) refer to this measure as *narrow offshoring* (FHN), and the authors claim FHN is the best indicator by virtue of its correspondence to the definition of offshoring as a process taking place within the industry. The formal expression of the FHN is:

$$OFFSH_{i,j,t}^{FHN} = \frac{Imported\_Int\_Inputs_{i,k\neq j,t}}{Total\_Int\_Inputs_{i,j,t}} \tag{9}$$

where i stands for the industry, j for country and t for time.[11]

To sum up, the dataset is a comprehensive panel that encompasses four periods and the years 1995 to 2010 across five major European countries.

3.2 Descriptive Evidence

The following sub-section relates descriptive evidence of the main variables and relationships studied here.

Table 2. Descriptive statistics

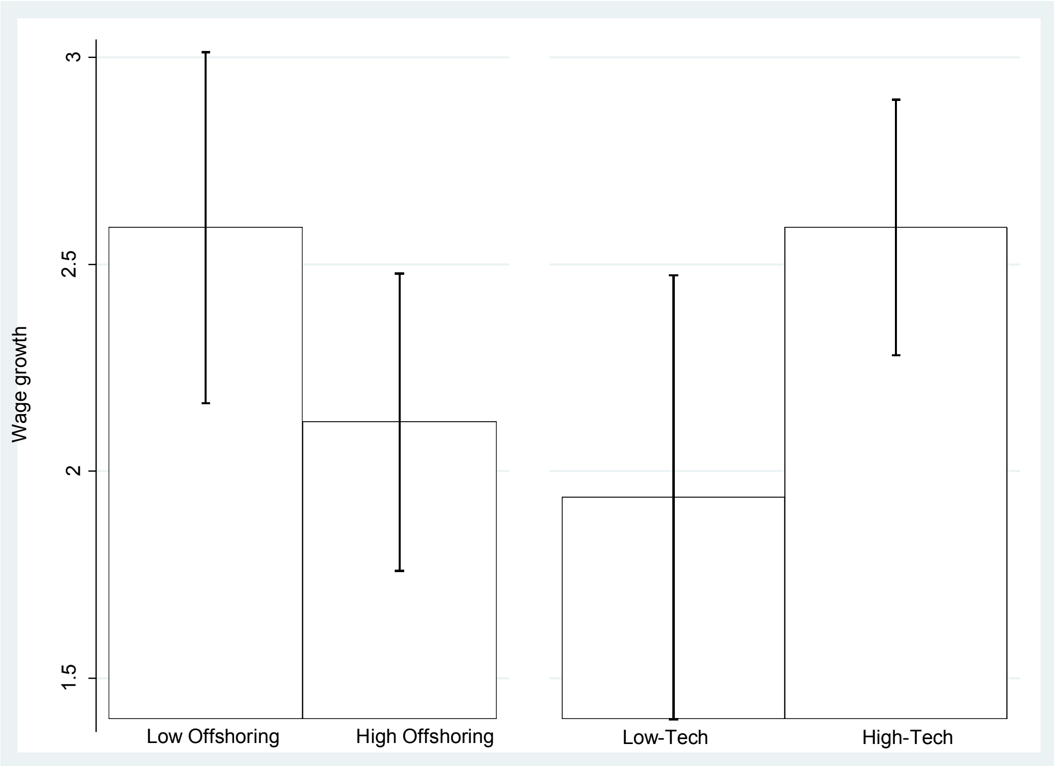
Variable	Statistics	Whole sample
Wages (%)	Mean	2.35
	Std. Dev.	3.18
Profits (%)	Mean	2.51
	Std. Dev.	2.05
R&D per employee	Mean	2.63
	Std. Dev.	4.86
New Mach. per employee	Mean	1.63
	Std. Dev.	2.27
Narrow Offshoring	Mean	1.74
	Std. Dev.	0.79
Average firm size	Mean	0.34
	Std. Dev.	1.71

Source: Compound average annual rate of variation, whole sample (DE, IT, ES, FR, UK, 1995-2010). Sectoral Innovation Database (Pianta et al., 2011). Note: Wages are sectoral wages per worked hours, Profits are the sectoral aggregated gross operating surplus. R&D expenditure and Expenditure for new machineries are expressed in thousands of euros for employee. All the variables are in euros and in real terms. Average firm size is computed dividing sector total employment by the number of firms in the sector.

Table 2 reports the main descriptive statistics for the key variables computed over the whole sample of industries. Figures 1 and 2 display the annual growth rate of sectoral wages according to the intensity of offshoring performed. Sectors are divided in two groups, where a threshold is considered the annual median of the discriminant variable.

[11] This indicator is highly correlated with other measures of offshoring. In particular, the Pearson rho between FHN and the Feenstra and Hanson broad indicator is .83 (p<.0001); between FNH and the high-tech offshoring indicator of Guarascio et al. (2014 and 2015), it is .77 (p<.0001); between FNH and the low-tech offshoring indicator, it is .75 (p<.0001). The correlation between FNH and the FNH limited to manufacturing is .76 (p<.0001).

Figure 1. Mean annual rate of change of wages by intensity of offshoring and R&D (1996-2000; 2000-2003; 2003-2007; 2007-2010)

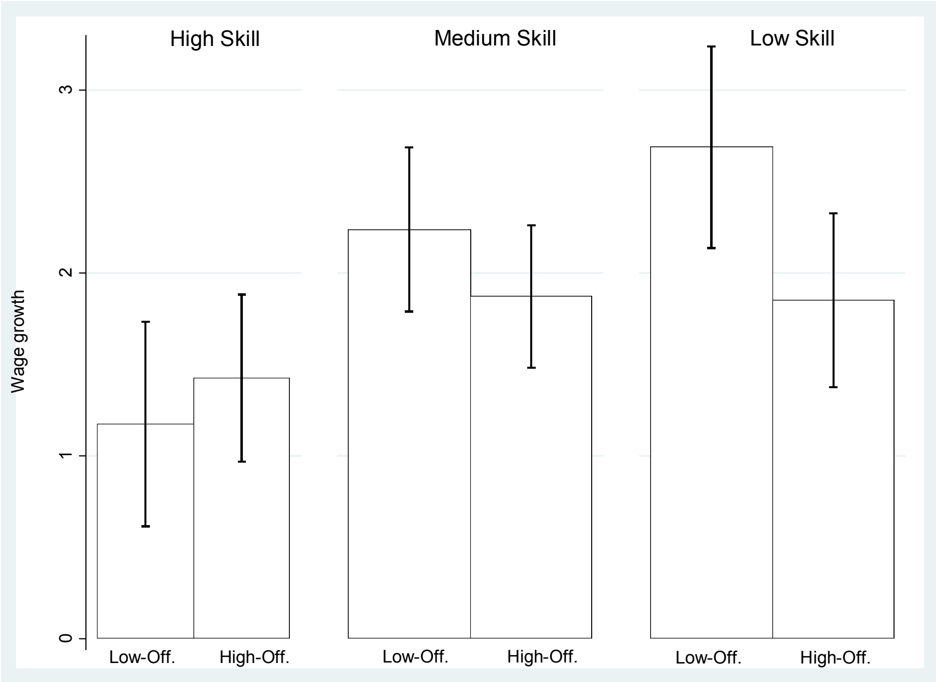


Source: Sectoral Innovation Database (Pianta et al., 2011).

The "high offshoring" group includes all sectors registering above-median FHN offshoring index (8); conversely, the "low offshoring" group is characterized by below-median offshoring index. Median has also been applied as a criterion for the classification of "high-tech" and "low-tech" sectors, with the former registering an above-median R&D expenditure and the latter a below-median R&D expenditure.

In addition, we apply the Wilcoxon rank-sum on the data; for the test, the null hypothesis is the equality of distribution of wage growth between high and low offshoring sectors (high and low R&D, respectively). As reported in Figure 1, a high level of offshoring is associated with lower wage growth (compared to those sectors with lower offshoring intensity). In particular, according to the results of the Wilcoxon rank-sum test, offshoring intensity drives wages downward ($z=1.7$, $p=0.08$). Conversely, technology pushes wages because workers can take some of the extra rents gained at the industry level after the introduction of new products. Generally speaking, the data show that high-tech sectors have higher wage growth ($z=-2.77$, $p=0.00$).

Figure 2. Mean annual rate of change of wages by intensity of offshoring and skill group (1996-2000; 2000-2003; 2003-2007; 2007-2010)

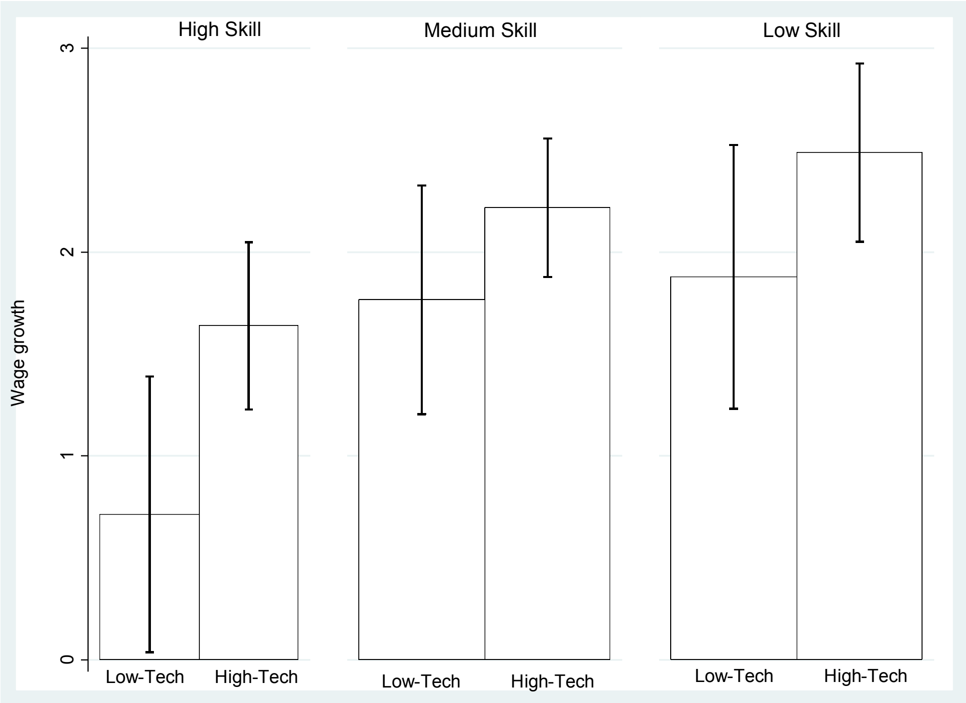


Source: Sectoral Innovation Database (Pianta et al., 2011). Low-Off. and High-Off. for high and low level of sectoral offshoring.

Figures 2 and 3 provide further evidence of the impact these variables have on different skill categories. Figure 2 makes manifest the downward pressure on wages for low skilled workers exerted by offshoring (z=2.25, p=0.02), while the offshoring effect is not significant for medium- (z=1.20, p=0.20) and high-skill (z=-0.68, p=0.49). Nevertheless, all three skill groups experience the technology wage premium (Figure 3), even if the distribution of wage growth per R&D level is statistically different for high (z=-2.77, p=0.00) and low (z=-2.0, p=0.04) and not statistically different for medium-skill categories (z=-1.45, p=0.14).

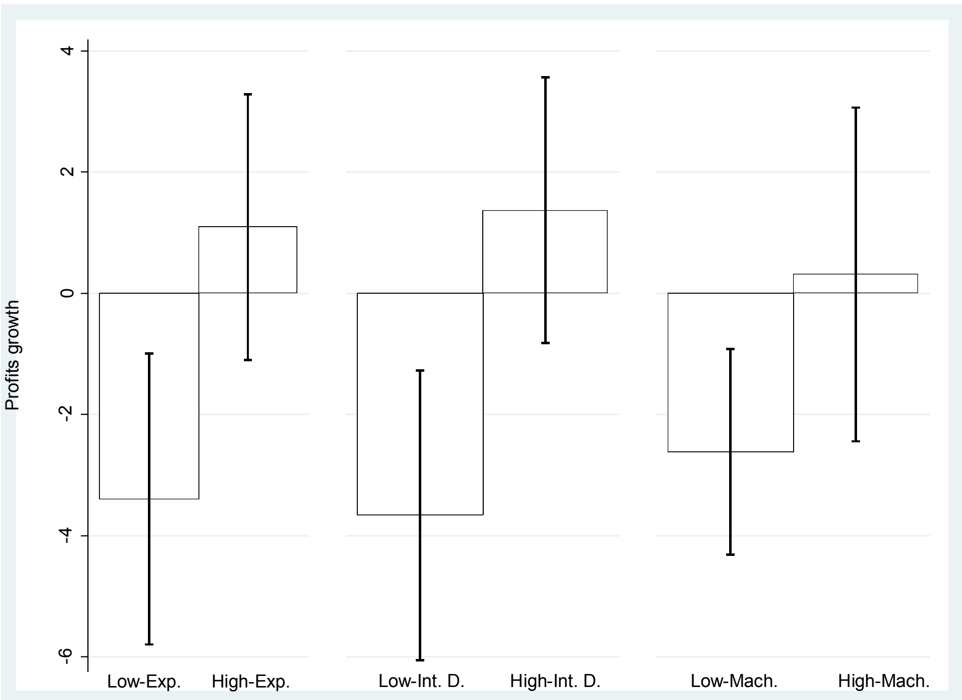
Overall, while offshoring drives wages downward, technology acts as a sort of counterpoise in that it pushes wages up (though mostly for high- and low-skill categories). In our empirical investigation, we show that despite a clear-cut "class conflict" between capital and labour, once the latter is disaggregated according to skill level, a more complex pattern of wage-profits relationships emerge.

Figure 3. Mean annual rate of change of wages by intensity of R&D and skill group (1996-2000; 2000-2003; 2003-2007; 2007-2010)



Source: Sectoral Innovation Database (Pianta et al., 2011). Low-Tech and High-Tech for high and low technology sectors.

Figure 4. Mean annual rate of change of profits by typology of demand – internal, external, investments (1996-2000; 2000-2003; 2003-2007; 2007-2010)



Source: Sectoral Innovation Database (Pianta et al., 2011). Low-Exp. and High-Exp. for high and low level of exports, Low-Int. D. and High-Int. D. for high and low level of internal demand and Low-Mach and High-Mach for low and high level of machinery.

Turning to profits dynamics, Figure 4 depicts the relation between their growth and a) demand—external and internal—and b) embodied technical change (expenditure on new machinery). Sectors characterized by sustained demand growth experience profits growth, for actual profits depend on potential profits (surplus) realized through demand. The difference in profits growth by size of demand growth is always statistically significant (external demand growth z=-5.60, p=0.00; domestic demand, z=-3.05, p=0.00). Similarly, embodied technological change positively affects profits growth (z=-1.78, p=0.02).

Of the three variables reported in Figure 4, exports and internal demand seem to be the major drivers of profits growth.

3.3 Econometric Strategy

Consider the following system:

$$\log(W_{it}) = \alpha_1 log(L_{it-1}) + \alpha_2 log(Y_{it-1}) + \alpha_3 log(R\&D_{it-1}) + \alpha_4 \log(OFF_{it-1}) + \alpha_5 log^2(R\&D_{it-1}) + \alpha_6 \log(R\&D_{it-1} * OFF_{it-1}) + \alpha_7 log^2(OFF_{it} - 1) + e_{it} \quad (10)$$

$$\log(P_{it}) = \alpha_1 \log(SIZE_{it}) + \alpha_2 log(I_{it}) + \alpha_3 log(C_{it}) + \alpha_4 \log(EXP_{it}) - \alpha_5 \log(W_{it}) + \varepsilon_{it}$$

The dependent variables are: variation of total sectoral profits and change of wage per worked hours. Though a more specific investigation of rates of return on capital may be pertinent, the lack of data on the fixed capital assets of industries makes such analysis unfeasible. Yet, working under the assumption that capital stock does not change rapidly at the industry level, it is reasonable to expect the variation of total profits to serve as a good proxy for capital returns. On the contrary, the wage bill directly depends on the number of hours worked. Therefore, to properly identify the relationship between labor remuneration, innovation and offshoring, the hourly wage is more appropriate for the present analysis (Pianta and Tancioni, 2008).

The system in (10) is triangular since the dependent variable in the first equation—the average annual change in wages—appears on the RHS in the second equation, which helps explain the change in profits. The identification strategy is articulated below.

To capture the effects of the covariates under OLS, strong exogeneity is required, i.e. exogeneity with respect to the random terms and absence of feedback from the unobservables to covariates. To mitigate the severity this problem, we initially calculate first differences for all variables in both rows of the system in (10). Such a step removes the time invariant part. As spelled out in Section 2, we calculate long differences with three- to four-year lags in order to harmonize the differences in data structure between CIS and other data sources. Long differences of this nature allow us to soften the autoregressive character of variables; likewise, they prove suitable for use as reliable instruments when dealing with endogeneity problems (Caroli and Van Reenen, 2001; Piva et al, 2005).

From there, in accordance with first difference specification, identification demands the regressors be orthogonal to the innovation in the random errors term and no longer be free of feedback. This identification restriction is achieved in the wage equation by considering the first lag of the variables for RHS – R&D intensity, offshoring, change in employment and gross output. Econometrically, the use of covariates at their first lag is crucial, given that doing so avoids any risk of endogeneity related to variable simultaneity.

Next, we establish estimates for the profits equation. Here, endogeneity is induced by the contemporaneity of demand components (and wage) to the innovation in the standard error. [12] As a result, we use a double instrumental variable approach to achieve consistency in the estimation of the second equation in (10). To begin, we employ standard IV approach instrumenting regressors using the lag structure (more precisely, the set of instruments includes the lagged rate of change of variables, of lagged value added, country, Pavitt and time dummies). Then, we use the novel heteroskedasticity-IV technique proposed by Lewbel (2012). The aforementioned method provides identification in mismeasured regressor models, triangular systems and simultaneous equation systems. Identification comes from a heteroskedastic covariance restriction that has been shown to be a feature of many endogeneity or mismeasurement models. Lewbel's technique (2012) opens up the possibility of identifying structural parameters in regression models with endogenous or mismeasured regressors in the absence of traditional identifying information such as external instruments or repeated measurements. In this context, identification is achieved via regressors not correlated with the product of heteroskedastic errors, which is part of many models whose error correlations can be traced to an unobserved common factor. The greater the degree of scale heteroskedasticity in the error process, the higher the correlation between the generated instruments and the included endogenous variables (these are the dependent variables in the auxiliary "first stage'" regressions). We can highlight two strengths to this approach: i) the identification assumption can be tested with a heteroskedasticity test (Breusch-Pagan test); ii) the availability of multiple instruments makes an over-identification test possible.

In this second step, an estimation of the potential effect of omitted variables is performed. Following Oster (2015) and Gonzales and Miguel (2015), this sensitivity analysis basically aims to infer the potential impact of omitted variable bias from the stability of the coefficients of

[12] As in the case of the technological and offshoring variables in the wage equation, the variable capturing embodied technical change in the profits equation is considered at its first lag. This choice reflects the hypothesis of the time lag needed for technology to exert its effects and, as was true for the wage equation, avoids the risks associated with simultaneity-related endogeneity.

interests when further controls are added. Based on the key (unverifiable) assumption that the selection on observables is the same as the selection on unobservables, after adjusting for differences in the variance of these distributions, we can calculate the bias and estimate the value of the coefficient after correcting for the bias. The formula for this coefficient is:

$$\bar{\bar{\alpha}} = \hat{\alpha}^* - (\hat{\alpha} - \hat{\alpha}^*) * \frac{R_{max} - R^*}{R^* - R^o} \quad (11)$$

where, $\hat{\alpha}^*$ and R^* are the coefficient estimate and R squared from the regression using observable covariates, and $\hat{\alpha}$ and R^o are the coefficient and R squared from the uncontrolled regression. The key to understanding this procedure is the R_{max}: the R squared when y is regressed against both observable and unobservable controls, which is clearly unknowable and is a degree of freedom. In our investigation, we have heeded the suggestions made by Gonzales and Miguel (2015), calculating four different scenarios: (1) a conservative scenario where $R_{max} = 1$, which would be the case given zero measurement error; (2) a scenario where $R_{max} = 2R^* - R^o$, which corresponds to the assumption that the relationship between the treatment and the observables is the same as the relationship between the treatment and the unobservables (Bellows and Miguel, 2009); (3) Oster's (2015) proposal of $R_{max} = Min\{2.2R^*, 1\}$; and, finally, (4) a rule of thumb $R_{max} = .8$, which corresponds to a measurement error of 20%.

The baseline single equation estimations are performed using the Weighted Least Squares (WLS) estimator. The WLS entails weighing each observation with the number of employees in the industry, as done in Bogliacino and Pianta (2013a). This method grants control over the heterogeneous contribution in terms of information provided by industry level data—grouped data of unequal size.

Moreover, we have gone a step further and added an alternative route to identification: we estimate the structural system of equation through Three Stage Least Squares (3SLS). In this case, the instruments are: endogenous variable lags, value added lag and a set of dummies capturing country- and industry-level heterogeneity.

Lastly, we investigate how the dynamics of profits and wages are reshaped across skill groups. We apply the 3SLS model after splitting industry wages up into high-, medium-, and low-skilled groups (per ISCED categories).

4. Results

4.1 Main Results

In this section, we present the results of the empirical analysis conducted on our panel of European industries.

As explained in the previous section, we proceed sequentially. Table 5 contains the wage equation estimation; Table 6 reports the profits equation estimation. All estimations have been performed with White-Huber heteroskedasticity robust standard errors.[13]

The results in Table 5 underscore the importance of innovation—proxied here by R&D efforts—and offshoring as drivers of industry wage dynamics and the non-linearity of these dynamics. The growth of sectoral wages is significantly linked to R&D efforts, as evinced when using the baseline WLS estimation. In fact, the relation between wages and innovation seems to be characterized by an "inverted U-shape effect." Such an effect is identified by the negative and significant sign of the coefficient for the squared R&D expenditure per employee. This effect can be explained by the presence of diminished wage sensitivity to the rent sharing mechanism.

As expected, offshoring exerts downward pressure on wages. The coefficient related to the narrow offshoring index (calculated for the initial year with respect to the dependent variable period of variation) is negative in sign for both specifications. Tellingly, the coefficient remains statistically significant when dummy variables are included (second column—Table 5). The effect of offshoring on wages is also non-linear. In contrast to the "inverted U-shape effect" observed in the case of the innovation-wages relation, offshoring has a negative and convex impact on wages.

The interaction between R&D efforts and offshoring is negative and statistically significant, thus implying that innovation and reorganization—in conjunction—tend to reduce wages.

Turning our focus to the wage equation's other variables, results do not deviate from expectations: in the baseline WLS model, lagged change in employment and gross output have coefficients which are, respectively, negative (but not significant) and positive (and significant).

The results in Table 5 prove robust in the face of various controls. First, we test the strength of the relations between technological change and wages using different CIS innovation variables in place of the R&D expenditure per employee—namely, QINNOV (share of innovative firms within the sector), QINPDT (share of product innovators), QEMAR (share of firms introducing products new to both the firm and the market) and QSENT (share of firms introducing innovation relying on internal resources). Readers are directed to Table A1 in the Appendix for more information on the robustness of innovation when using alternative measurements.

Second, the equation is run with alternative measures of human capital to control for the possibility of omitted variables in the measurement of innovation and offshoring. Alternatives used are share of workers with secondary and tertiary degree (ISCED classification) and share

[13] For the profits equation, the Breusch-Pagan statistic is Chi2(1)=77.43 ($p<.01$); for the wage equation, it is chi2(1)=31.04 ($p<.01$). We have used a diagnostic test to check multicollinearity; results show this concern can be ignored, for the variance inflation factor is 1.04 for the profits equation and 3.43 for the wage equation.

of managers and qualified personnel (ISCO categories). Readers are directed to Table A2 in the Appendix for more information on the robustness when using these alternatives.

Thirdly, we replicate the estimation using the change in wages per employee as a dependent variable. No significant differences emerge (see Table A3 in the Appendix).

Profits equation results estimated with the WLS, IV and the heteroskedasticity-IV estimator (Lewbel, 2012) are found in Table 6. The negative impact of wages on profits is strong and significant across estimations. The WLS estimation (first column—Table 6) shows that both domestic demand and exports are positive drivers of profits growth. Nevertheless, such results may be biased by various sources of endogeneity, such as omitted variables or simultaneity of wage, demand components and unobservables.

Therefore, columns (2) and (3) represent our benchmark; in these columns, we utilize instrumental variables. The use of instruments leads to a partial confirmation of the results obtained with the WLS. For instance, an increase in wages continues to negatively impact profits. Looking at demand variables, in both the IV and the heteroskedasticity-IV specifications, domestic demand loses significance while exports turn out to be the strongest profits driver. Together, these results fit with previous findings by Bogliacino and Pianta (2013a). Surprisingly, it seems that no role in explaining profits can be attributed to lagged investments (proxied by expenditure on new machinery and related to the embodied technical change hypothesis) or firm size (which proxies the degree of market competitiveness).

The validity of the proposed instruments is not rejected: in column (2), we run the Sargan-Hansen test, which does not reject the null of over-identifying restrictions (p=.29). In column (3), we report the heteroskedasticity test validating the added instruments[14] and the over-identification test, which does not reject the null of absence of correlation between the over-identifying instruments and standard errors (p=.23).

The presence of misspecification is rejected by means of a Ramsey test (F(3, 384)=1.59; p=.19). In Table A4 (Appendix), the baseline equation is performed with the share of managers as an additional level of control—doing so proxies managerial ability likely to affect profits dynamics. No significant changes are observed.

Finally, we run a sensitivity analysis on the inclusion of contemporaneous variables in the profits equation as proposed by Oster (2015). These results are presented in Table A5 (Appendix) using different values of R_{max}—the maximum R squared in an ideal regression of outcome over observables and unobservables. Additionally, the table contains an estimation of

[14] In Lewbel's (2012) framework, the greater the degree of scale heteroskedasticity in the error process, the higher the correlation between the generated instruments and the included endogenous variables, which are the regressands in auxiliary regressions. To ensure the reliability of the adopted procedure, we perform the auxiliary regressions—compound rate of change of demand and exports against all the instruments— separately, thus testing for the presence of heteroskedasticity. The results of the Breusch-Pagan test (Table 6) reinforce the validity of the strategy employed here.

the coefficient after correcting for bias. We are primarily interested in determining whether the interval composed by the estimated coefficient and the coefficient corrected for omitted variable bias is bounded away from zero. This turns out to be the case for both the wage and export coefficients, which supports the hypotheses of bargaining conflict, and export realization profits, respectively.

Table 5. The wages equation

Dependent Variable: Compound average rate of change of wages per worked hour.
WLS with White-Huber robust standard errors and weighted data (weights are the numbers of employee in the sector)
Robust standard errors in brackets: * p<.10, ** p<.05, *** p<.01.

	(1) WLS model	**(2) WLS with dummies**
R&D expenditure (first lag)	0.55	0.38
	[0.08]***	[0.07]***
R&D expenditure squared (first lag)	-0.30	-0.00
	[0.00]***	[0.00]***
Offshoring (first lag)	-0.18	-0.26
	[1.17]	[0.14]*
Offshoring squared (first lag)	6.13	3.35
	[3.50]*	[2.84]
R&D*Offshoring (first lag)	-0.02	-0.02
	[0.01]*	[0.01]
Δ Sectoral employment (first lag)	-0.01	0.02
	[0.03]	[0.03]
Δ Sectoral gross output (first lag)	0.14	0.05
	[0.03]***	[0.03]
Country, Pavitt and time dummies		Yes
N.observations	413	413
R2 (Adj)	0.23	0.35

Now, a discussion of 3SLS estimation results. In order to control for all possible sources of heterogeneity, each equation is estimated including country and sectoral dummies. Demand variables (domestic demand and exports) are instrumented using the first lag of the endogenous regressors, lagged (sectoral) value added and time dummies.

Table 7 reports 3SLS estimation,[15] which further reinforces the findings in Tables 5 and 6. The first column (of Table 7) contains the wage equation's estimation, once again highlighting the contrasting role of innovation and offshoring. While innovation pushes wages upward, the coefficient associated with offshoring is negative in sign (even if not significant) when considered alone and when in interaction with lagged R&D efforts.

[15] In order to ensure there is no risk of biases in the results, we have tested the 3SLS baseline model (Table 7) without observations from the last (crisis) period, 2007-2010. All identified relationships prove to be robust to such validation procedure.

Table 6. The profits equation

Dependent Variable: Compound average rate of change of total sectoral gross operating surplus

WLS with White-Huber robust standard errors and weighted data (weights are the numbers of employee in the sector), IV (endogenous regressors: compound rate of change of domestic demand and compound rate of change of exports; instruments: first lag of the endogenous regressors, lagged sectoral value added, country, time and Pavitt dummies), augmented IV-OLS (endogenous regressors: compound rate of change of domestic demand and compound rate of change of exports; instruments: first lag of the endogenous regressors, lagged sectoral value added, country, time, Pavitt dummies and generated instruments). The Sargan overidentification test refers to augmented IV-OLS estimation. Std. errors in brackets: * p<.10, ** p<.05, *** p<.01.

	(1) WLS model	**(2) IV**	**(3) Heteroschedasticity-IV**
ΔWages/worked hour	-1.53	-1.60	-1.52
	[0.52]***	[0.32]***	[0.26]***
Average firm size	-0.66	-0.34	-0.43
	[0.21]	[0.65]	[0.44]
Exp. for new mach. (first lag)	0.06	-0.08	0.04
	[0.44]	[0.56]	[0.55]
ΔDomestic demand	0.33	0.53	0.11
	[0.12]***	[0.35]	[0.15]
ΔExports	0.12	1.12	0.40
	[0.05]*	[0.32]***	[0.15]***
Country, Pavitt and time dummies	Yes		
N.observations	393	390	
R2 (Adj)	0.23		
Root MSE		27.05	23.84
Sargan overidentification test		Chi2(1)=10.79 (p=0.29)	Chi2(1)=9.20 (p=0.23)
Breusch-Pagan test on the first stage regression (Domestic demand)			Chi2(1)=25.21 (p<.01)
Breusch-Pagan test on the first stage regression (Exports)			Chi2(1)=58.57 (p<.01)

The inverted U-shape relation for the single equation estimations also appears in the system 3SLS estimation. With regard to economic variables, the lagged change in gross output is, not surprisingly, positively correlated with wages growth.

Moving to the profits determinants (second column), the negative relationship between wages and profits is observed again; the same holds for the role of demand. Finally, of the demand components, exports emerge as the strongest driver of profits growth.

In the following sub-section, 4.2, the heterogeneity of the impact of technology and offshoring across skills group is investigated by means of a structural 3SLS estimation, with wages classified in accordance with ISCED classification.

Table 7. The Wages-Profits 3SLS estimation (whole sample)

Dependent Variables: Compound annual rate of change of sectoral hourly wages and compound annual rate of change of total profits; time dummies included. 3SLS with White-Huber robust standard errors. Endogenous regressors: compound rate of change of domestic demand and compound rate of change of exports; Excluded instruments: first lag of the endogenous regressors, lagged sectoral value added, country and Pavitt dummies). Robust standard errors in brackets. * p<.10, ** p<.05, *** p<.01.

	ΔWages/hour	ΔProfits
R&D expenditure (first lag)	0.56 [0.11]***	
R&D expenditure (squared-first lag)	-0.01 [0.00]***	
Narrow Offshoring (first lag)	-0.23 [0.22]	
Narrow Offshoring (squared-first lag)	8.47 [4.27]*	
R&D expenditure * Narrow Offshoring	-0.02 [0.02]	
ΔEmployment (first lag)	-0.01 [0.02]	
ΔGross Output (first lag)	0.12 [0.04]***	
ΔWages/hour		**-1.66** **[0.51]***
Expenditure for new mach. (first lag)		0.00 [0.53]
ΔExports (instrumented)		0.95 [0.25]***
ΔDomestic Demand (instrumented)		0.58 [0.29]*
Time dummies	Yes***	Yes***
Observations	385	385
R2 (Adj)	0.22	0.34
RMSE	4.1	26.4

4.2 Impact Heterogeneity: Skills

In this sub-section, we estimate, using 3SLS, a simultaneous system with the rate of change of profits along with the change of wages divided into skill categories (high-, medium- and low-skills). Wage equations are regressed against the same covariates as in the pooled model reported in the previous section, with the exception of the employment variable (seeing as it is skill specific).

The reason for using this four-equation system betrays our aim to unpack the heterogeneous impact on profits that a change in high-, medium- and low-skilled wages may have, as well as to identify possible heterogeneity in the impact of technology and offshoring across skills. Here, the identification strategy mimics the one defined in the general model.

Categorizing wages according to worker skills produces a number of relevant findings. High-skilled wages (first column of Table 8) incorporate innovation rents, captured through lagged R&D expenditure, but, in this case, the effect seems to be linear. On the contrary, the narrow offshoring indicator is reversed in sign, though also statistically significant when compared to the pooled model. Such results reveal, as previously argued, that high-skilled workers benefit from offshoring dynamics (as opposed to being penalized by said dynamics). As has been asserted in Fosse and Maitra (2012) and Hummels et al. (2014), two channels are responsible for offshoring's favoring of high-skill workers: outsourcing (relatively) more labor-intensive parts of the production process, normally characterized by a greater reliance on low-skilled workers, could increase the demand for high-skilled jobs premised on keeping knowledge-intensive production in house. The squared value of the narrow offshoring indicator and the interaction term are not significant. The lagged change in employment and gross output are consistent with the pooled 3SLS estimates.

For medium-skilled wages (second column of Table 8), innovation has a positive impact and is characterized by the inverted U-shape relationship (also observed for the baseline estimation). Interestingly enough, offshoring's impact is not negative, which refutes the findings of Foster et al. (2012) in their analysis of medium-skilled employment growth. As in the case of high-skilled wages, the coefficients associated with the lagged change in employment and gross output match those obtained when using the pooled estimation.

Of particular importance is the evidence related to low-skilled wages (third column of Table 8). Our findings indicate that low-skilled workers do not benefit from innovation-related rents, as evidenced by the R&D coefficient's loss of significance for this wage group after producing positive and significant effect for the previous estimations. Also of note is the relation between offshoring activities and low-skilled wages: in contrast to high- and medium-skilled wages, offshoring has a negative and statistically significant impact on low-skilled wages. This is a crucial point, for SBTC predicts that the main impact of offshoring is on medium-skill wages (Acemoglu and Autor, 2011). Nonetheless, despite findings in the previous estimations, the interaction between R&D efforts and offshoring is negative and significant. In other words, in the case of low-skilled wages, the depressing effect of offshoring prevails over any possible innovation-related positive impact.

Finally, wages-profits dynamics are significantly reshaped when explicitly accounting for different skill groups (column four of Table 8). The conflict at the capital-labour level coexists with more heterogeneous dynamics at the disaggregate level. The negative impact on profits still applies only to medium-skilled wages, while high skilled wages are positively associated with profits, even if there is weak significance. For their part, low-skilled wages seem to have no effect on profit dynamics. These baseline results show that demand elements, especially exports growth, are again strong and significant profits drivers.

Table 8. The Wages-Profits 3SLS estimation (profits vs high, medium and low skilled wages)

Dependent Variables: Compound annual rate of change of sectoral high, medium and low skilled hourly wages; compound annual rate of change of sectoral profits. Time and country dummies included. 3SLS with White-Huber robust standard errors. Endogenous regressors: compound rate of change of domestic demand and compound rate of change of exports; Excluded instruments: first lag of the endogenous regressors, lagged sectoral value added, country and Pavitt dummies). Robust standard errors in brackets. * p<.10, ** p<.05, *** p<.01.

	(High skill) **ΔWages/hour**	(Med. skill) **ΔWages/hour**	(Low skill) **ΔWages/hour**	**ΔProfits**
R&D expenditure (first lag)	0.29 [0.14]*	0.44 [0.12]***	0.23 [0.13]	
R&D exp. (squared-first lag)	0.00 [0.00]	-0.01 [0.00]*	-0.00 [0.00]	
Narrow Offshoring (first lag)	0.70 [0.28]**	0.18 [0.23]	-0.55 [0.26]**	
Narrow Off. (squared-first lag)	-6.32 [5.51]	-4.19 [4.61]	6.8 [4.99]	
R&D exp. * Narrow Offshoring	-0.02 [0.03]	-0.03 [0.02]	-0.07 [0.03]**	
ΔEmployment (high skilled)	-0.05 [0.02]**			
ΔEmployment (medium skilled)		-0.05 [0.01]***		
ΔEmployment (low skilled)			-0.14 [0.01]***	
ΔGross Output (Rate of Growth)	0.10 [0.05]*	0.13 [0.04]***	0.39 [0.04]***	
ΔWages/hour (high skill)				1.66 [0.48]*
ΔWages/hour (med skill)				-4.03 [1.15]***
ΔWages/hour (low skill)				0.65 [0.90]
Exp. for new mach. (first lag)				0.03 [0.55]
ΔExports (instrumented)				1.21 [0.30] ***
ΔDom. Demand (instrumented)				0.68 [0.29] **
Time dummies	Yes***	Yes***	Yes***	Yes***
Obs	186	175	355	334
R2 (Adj)	0.31	0.13	0.52	0.36
RMSE	4.87	4.84	5.41	29.2

5. Conclusions

In this article, we have identified the effect of innovation, offshoring and demand on wage and profit dynamics. We sketch a model based on two key notions: (1) wages are bargained in accordance with a company's planning decisions, and the distributive conflict arises from a surplus to share (as in the *range theory of wages* developed by Howell, 1999) where both technology (R&D) and international organization of production (offshoring) to some extent define the distributive arrangement by shaping the bargaining power of the parties involved; (2) profits are realized if there is enough demand (per the standard principle of effective demand), and the effect is not necessarily homogeneous across different sources of demand.

Theoretically speaking, the present research builds on the rent-sharing hypothesis introduced by Van Reenen (1996) and later developed by Bogliacino (2014). The inclusion of offshoring among wage determinants has been pivotal for completing the picture of the "rent-sharing" bargaining scheme. A critical takeaway from our research is that, at present, offshoring is a key "weapon" used to threaten workers within the bargaining process.

Furthermore, our article provides two major contributions.

In the first place, the baseline model highlights a number of key relationships: the contrasting impact of offshoring—pushing wages downward—and innovation—pushing wages upward; the presence of a non-linear effect in the R&D-wages relation; social conflict, captured by the negative effect of wages growth on profits (see also Pianta and Tancioni, 2008); the fundamental role of demand, particularly exports, as a profits driver (Bogliacino and Pianta, 2013a).

In the second place, this article contributes to the empirical literature on offshoring's impact on wages classified according to worker skills (e.g. Feenstra and Hanson 1996, 1997; Grossman and Rossi-Hansberg 2007, 2008 and Hummels et al., 2014).

Put simply, the most noteworthy elements illustrated in our paper can be summarized as follows: to the best of our knowledge, the analysis undertaken here is the first attempt to measure the simultaneous impact of innovation and offshoring on wages by skill while still accounting for the wage-profits bargaining conflict.

By distinguishing three types of workers (high-, medium- and low-skills), we reached a number of important findings: a) consistent with the rent-sharing hypothesis formulated above, innovation spurs high- and medium-skilled wages, yet it is not correlated with low-skilled ones; b) high-skilled wages are found in relatively higher "offshoring intensive" industries, for they seem to benefit from the improved efficiency likely associated with production offshoring, while low-skilled wages tend to decrease in the same sectors, which points to the prevalence of a "threat effect" that hinders low-skilled worker's bargaining power (though this does not speak to the situation of medium-skill wages—see SBTC literature for more information); c) the interaction between R&D efforts and offshoring, which is not significant in all other specifications, has a negative and significant impact on low-skilled wages, thus confirming the downward pressure exerted by offshoring on these wages; d) the wages-profits relationship undergoes far-reaching changes when skills are taken into account—that is, high-skilled wages are correlated with profits growth, suggesting the presence of large innovation rents shared between the two, whereas medium-skilled have a negative impact, which is in keeping with the average impact, and, lastly, the growth of low-skilled wages has no effect on profits

Our identification strategy relies on instrumental variables, including Lewbel's (2012) recently proposed heterogeneity-based IV, and our results are robust to the presence of omitted variables. In terms of general implications, this study confirms the need for a more strictly regulated institutional system so as to ensure a smoother functioning of redistribution at the shop-floor level and simultaneously allow for a more predictable internal demand growth rate, one that would reduce the uncertainty related to capital accumulation and the pressure to increase profits share at the expense of labour.

In sum, the set of findings presented here emphasize the importance of skills in determining the patterns of the profits-wages dynamics, a finding which has clear distributive implications.

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Appendix

The Appendix provides the robustness check for the econometric model of profits and wages determinants.

Table A1 report the wage equation estimated using different innovation proxies drawn from the CIS survey.

Table A1. The Wages WLS estimation using different innovation variables
Dependent Variable: Compound average rate of change of wages per worked hour.
WLS with White-Huber robust standard errors and weighted data (weights are the numbers of employee in the sector)
Robust standard errors in brackets: * p<.10, ** p<.05, *** p<.01.

	(1) WLS model (Share of innovative firms as covariate)	**(2) WLS model (Share of product innovators as covariate)**	**(3) WLS model (Share of firms introducing products new to the market as cov.)**	**(4) WLS model (Share of innovators relying on internal resources as cov.)**
Techn. Change (first lag)	0.08	0.05	0.08	0.08
	[0.01]***	[0.01]***	[0.01]***	[0.01]***
Techn. Change (first lag)	-0.00	-0.00	-0.00	-0.00
	[0.00]**	[0.00]	[0.00]	[0.00]***
Offshoring (first lag)	-0.02	0.16	-0.17	-0.26
	[0.30]	[0.38]	[0.25]	[0.27]
Offshoring squared (first lag)	2.96	3.61	3.95	4.67
	[3.87]	[3.68]	[3.89]	[3.57]
Techn.Change*Offshoring (first lag)	-0.00	-0.00	-0.00	-0.00
	[0.00]	[0.00]	[0.00]	[0.00]
Δ Sectoral employment (first lag)	0.00	-0.00	0.00	0.00
	[0.03]	[0.03]	[0.03]	[0.03]
Δ Sectoral gross output (first lag)	0.06	0.07	0.06	0.06
	[0.03]*	[0.03]**	[0.03]*	[0.03]*
N.observations	433	492	467	467
R2 (Adj)	0.29	0.28	0.32	0.30

Table A2 presents the regression controlling for human capital: share of workers with secondary and tertiary education and the share of clerks and manager inside the workforce. The results in table A2 confirms the positive effect of R&D expenditure on wages which turns to be negative for the squared term. Conversely, offshoring reduces the average wage paid at the sectoral level. Surprisingly, it is the share of workers with secondary education which pushes up the average sectoral wage while an increase in the share of workers with tertiary education is negatively associated with the wage paid probably because the wage premium due to education is gained by a small amount of tertiary educated workers and it is not transferred to the average wage.

Table A2. The Wages WLS estimation controlling for human capital
Dependent Variable: Compound average rate of change of wages per worked hour.
WLS with White-Huber robust standard errors and weighted data (weights are the numbers of employee in the sector)
Robust standard errors in brackets: * p<.10, ** p<.05, *** p<.01.

	(1) WLS model	**(2) WLS model**
R&D expenditure (first lag)	0.35	0.39
	[0.11]***	[0.10]***
R&D exp. squared (first lag)	-0.00	-0.00
	[0.00]*	[0.00]**
Offshoring (first lag)	-0.25	-0.23
	[0.15]*	[0.14]
Offshoring squared (first lag)	2.37	2.73
	[2.91]	[2.75]
R&D*Offshoring (first lag)	-0.02	-0.02
	[0.01]	[0.02]
Δ Sectoral employment (first lag)	0.02	0.02
	[0.04]	[0.04]
Δ Sectoral gross output (first lag)	0.04	0.06
	[0.03]	[0.04]*
Share of workers with tertiary educ.	-0.3	
	[0.01]*	
Share of workers with secondary educ.	0.02	
	[0.01]*	
Share of managers		-0.00
		[0.01]
Share of clerks		-0.01
		[0.01]
Sectoral Pavitt dummy		
N.observations	413	413
R2 (Adj)	0.36	0.35

Table A3 provides the results of the estimation performed using wages per employee in place of wages per worked hours as dependent variable. There are no major changes.

Table A3. The Wages WLS estimation (robustness check)

	ΔWages/employee
R&D expenditure (first lag)	0.23
	[0.09]***
R&D expenditure-squared (first lag)	-0.00
	[0.00]
Offshoring (first lag)	-0.13
	[0.22]
Offshoring-squared (first lag)	2.49
	[3.33]
R&D expenditure*Offshoring (first lag)	-0.00
	[0.02]
Δ Sectoral employment (first lag)	0.04
	[0.05]
Δ Sectoral gross output (first lag)	-0.01
	[0.07]
Pavitt, time and country dummies	Yes
Observations	413
R2	0.27
Prob > F	0.0000

Dependent Variables: Compound annual rate of change of sectoral hourly wages
Std. Errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

In Table A4 below, the outcome of the profits equation estimation implemented including the share of managers and clerks within the sector is reported.

Table A4. The profits equation

Dependent Variable: Compound average rate of change of total sectoral gross operating surplus

WLS with White-Huber robust standard errors and weighted data (weights are the numbers of employee in the sector), IV (endogenous regressors: compound rate of change of domestic demand and compound rate of change of exports; instruments: first lag of the endogenous regressors, lagged sectoral value added, country, time and Pavitt dummies), Robust standard errors in brackets: * p<.10, ** p<.05, *** p<.01.

	(1) WLS model	(2) IV
ΔWages/worked hour	-1.44	-1.43
	[0.20]***	[0.34]***
Average firm size	-0.37	-0.25
	[0.31]	[0.65]
Exp. for new mach. (first lag)	0.30	0.30
	[0.48]	[0.61]
ΔDomestic demand	0.35	0.62
	[0.12]***	[0.30]
ΔExports	0.10	1.05
	[0.07]	[0.0.28]***
Share of managers	0.02	-0.039
	[0.07]	[0.06]
Share of clerks	-0.12	-0.03
	[0.17]	[0.09]
N.observations	393	390
R2 (Adj)	0.14	

In Table A5 below we provide the sensitivity of the coefficients of the contemporaneous variables in the profits equation to the bias that may be induced by omitted variables. The methodology is explained in Section 3.3, while the results are discussed in Section 4.1.

Table A5. The profits equation: test on omitted variable bias

Source: The Table refers to the impact of wages (panel A), domestic demand (B), and export (C) in the profits equation. alfa* and R* are the coefficient estimate and R squared from the regression using observable covariates, and alfa^o and R^o are the coefficient and R squared from the uncontrolled regression. Rmax is the R squared of a regression of the outcome variables over observables and unobservables. In C Rmax=1 (zero measurement error); in BM, Rmax =2R*-R^o (Bellows and Miguel, 2009); in O, Rmax=Min{2.2R*,1} (Oster, 2015), and, finally, in R, Rmax=.8 (measurement error equal to 20%). Alfa corrected is the estimated coefficient after the correction for the bias (see equation 11 in section 3.3).

(A) Wage	BM	OS	C	R
alfa*	-1.23	-1.23	-1.23	-1.23
alfa^o	-0.71	-0.71	-0.71	-0.71
R*	0.174	0.174	0.174	0.174
R^o	0.02	0.02	0.02	0.02
Rmax	0.328	0.3828	1	0.8
alfa corrected	-1.75	-1.94	-4.01	-3.34
(B) Domestic demand	BM	OS	C	R
alfa*	0.26	0.26	0.26	0.26
alfa^o	0.38	0.38	0.38	0.38
R*	0.174	0.174	0.174	0.174
R^o	0.041	0.041	0.041	0.041
Rmax	0.307	0.3828	1	0.8
alfa corrected	0,14	0,07	-0,49	-0,30
(C) Export	BM	OS	C	R
alfa*	0.13	0.13	0.13	0.13
alfa^o	0.04	0.04	0.04	0.04
R*	0.174	0.174	0.174	0.174
R^o	0.004	0.004	0.004	0.004
Rmax	0.328	0.3828	1	0.8
alfa corrected	0,22	0,24	0,57	0,46