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The *good jobs-high innovation* virtuous circle

Mario Pianta[1,*], Jelena Reljic [2,3]

[1] Scuola Normale Superiore (Classe di Scienze Politico-Sociali), Florence, Italy

[2] Sant'Anna School of Advanced Studies (Institute of Economics), Pisa, Italy

[3] Sapienza University of Rome (Department of Economics and Law), Rome, Italy

[*] Corresponding author: mario.pianta@sns.it

Abstract

This article investigates the existence of a virtuous circle between industries' employment quality, their ability to introduce new products, increase labour productivity and pay higher wages. We develop a simultaneous four-equation model investigating empirically four related variables: first, the rise of non-standard work as a proxy of low employment quality; second, the success in developing new products and services; third, labour productivity growth; fourth, wage increases. The model is tested empirically for 41 manufacturing and service sectors of six European economies (Germany, France, Italy, Spain, the Netherlands, and the UK) over the period 1996-2016. The findings provide novel evidence of mutually reinforcing relationships, where higher employment quality complements technological activities, leading to more product innovations that increase productivity growth. In turn, the latter allows wage increases that contribute to higher employment quality. These combined moves towards higher-quality labour and higher-quality capital are at the root of what we define as the *good jobs-high innovation* virtuous circle.

JEL classification: J23, J24, J31, L6, L8, O31, O33, O52

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1. Introduction

The relationships between labour, technology, productivity, and wages have been usually investigated in separate ways, without an integrated approach. Different streams of literature have examined the drivers of innovation, economic performance, the determinants of the quantity and quality of employment and wages, focusing on the specificity of the issues and neglecting the broader interactions between these economic processes.

The aim of this article is to propose a virtuous circle model where the positive relationships in each of these fields feed on each others, leading to a cumulative process of change, and - possibly - to a *good jobs-high innovation* trajectory. In order to investigate these relationships in a more integrated way, considering not only one-way relationships but their interdependencies as well, we develop and test a simultaneous equation model at the level of industries.

The *good jobs-high innovation* virtuous circle is depicted in Figure 1. First, high employment quality is complementary to R&D efforts and contributes to greater product innovation - the outcome of a strategy of *technologal competitiveness*. Second, product innovation is a key driver of labour productivity growth, alongside improved capital and labour inputs. Third, productivity gains are translated into higher wages and higher profits, distributing the benefits of growth. Finally, high wages in turn lead to improvements in the quality of jobs - with higher skills and more widespread standard employment positions - and stimulate greater innovation efforts. In this way the virtuous circle brings the economy to a higher growth trajectory and benefits all economic actors. In developing this model, we have to consider the high heterogeneity of economic activities; innovation, labour markets and productivity are crucially affected by structural factors and the diversity of sectors. Therefore, an appropriate focus for this investigation is the industry level; these processes however operate also - with greater heterogeneity - at the firm level and additional investigations may address the presence of virtuous circles in firms.

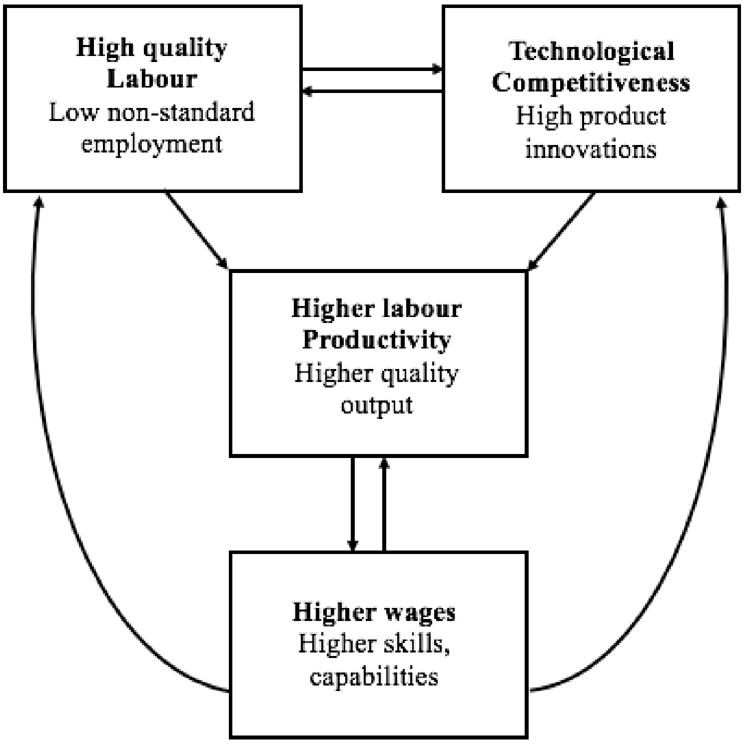
In developing this approach we connect different streams of research and build a more integrated perspective.

Non-standard jobs and innovation. Studies on industries and firms have investigated the impact of non-standard jobs (e.g. temporary, part-time, agency work), employment protection and job turnover on different measures of innovation and economic performances, recognising that labour market flexibility is generally negatively associated to innovation outcomes (Michie and Sheehan 2003; Cetrulo et al. 2019, Kleinknecht et al. 2014, Reljic et al. 2021) and productivity (Lisi and Malo 2017, Lucidi and Kleinknecht 2010; Ortega and Marchante 2010).

Efforts to explore the job quality-innovation nexus in a more integrated way have been developed by Duhautois et al. (2018) who found a positive association between technological innovation and job quality at the level of countries, industries and individuals; additional factors affecting job quality include education, type of occupation and the presence of employee representation.

Technology and productivity. A large body of literature has explored the impact of technological activities - R&D, innovation and patents - on various measures of productivity - from total factor productivity to labour productivity (see Hall 2011 and Ugur and Vivarelli 2021 for literature reviews) - identifying a significant contribution of innovation to improved economic performance. However, the diversity of strategies behind technological efforts has often been ignored, both in the case of R&D (Syverson 2011; Sterlacchini and Venturini 2013), and innovation; Pianta (2001, 2018) showed that two main innovation strategies can be identified, with distinct effects on productivity - the search for *technological competitiveness* through new product and services, as opposed to *cost competitiveness* efforts through the adoption of labour-saving technologies.

Figure 1. The virtuous circle between high quality labour, technological competitiveness, productivity and wages



Source: Authors' illustration

A useful contribution has come from Crépon et al. (1998) who developped a structural model where R&D efforts lead to innovation, and innovation translates into productivity growth. This model has been widely used at firm and industry level in the empirical innovation literature (see Mohnen and Hall 2013 for a review). However, the model has a static approach, leading to cross-sectional investigations of firms or industries, disregarding the presence of lags and feedback effects.

A dynamic approach has been proposed by Bogliacino and Pianta (2013) who investigated empirically the existence of a virtuous circle of technological progress using a simultaneous model of three equations at industry level. Their results show that lagged R&D investments translate into successful product innovations that lead to higher profits, that are in turn reinvested into further R&D efforts, suggesting a feedback effect from retained earnings to new products. Bogliacino et al. (2017) tested the same model on Italian firms and found that the virtuous circle can be identified for the small group of persistent innovating firms alone. Exploring a panel of French and Dutch manufacturing firms Raymond et al. (2015) found that innovation contributes to productivity but with no feedback effects, suggesting that more productive firms are not necessarily more successful innovators.

Productivity and wages. Different views exist on the productivity-wages nexus. Standard economic theory states that firms hire workers until the real wage equals the marginal product of labour; wage increases are driven by rises in marginal productivity. Conversely, the efficiency wage theory suggests that higher wages stimulate greater productivity (Akerlof and Yellen 1990, Shapiro and Stigliz 1984). In addition, evolutionary perspectives point out that higher industry-wide wages might spur technological change as firms have to innovate to compensate for labour costs, while non-innovators exit the market (Nelson and Winter 1982). Building on these insights, we explore the link between productivity and wages, and the presence a of lagged 'wage push' effects on labour productivity.

Against this background, we aim to investigate these relationships in a more integrated way, taking into account the interdependencies among variables. We therefore develop and test a simultaneous equation model that links four key variables: employment quality, technological competitiveness, labour productivity and wages. The four equations of the model are presented in the next section. The empirical test is carried out at the industry level for 41 manufacturing and service sectors in six European economies - Germany, Spain, France, Italy, the Netherlands and the UK - over the 1994–2016 period, using the new version of the Sectoral Innovation Database with the NACE Rev.2 classification (Pianta at al. 2021).

Our approach offers several novelties. First, we consider the quality of jobs as a determinant of innovation performance, pointing out the complementarity between labour competences, R&D and other innovation inputs. Building on evolutionary perspectives, we expect that the diffusion of non-standard forms of employment - and the high labour turnover it entails - disrupts the accumulation of knowledge required for successful innovations, leading to a loss of the tacit knowledge 'embodied' in workers (Nelson and Winter, 1982). This role of job quality has so far received little attention by the innovation literature.

Second, we emphasise the role of *technological competitiveness*, based on product innovation, as a driver of productivity growth, complementary to the role played by improvements in capital and labour – proxied by fixed investment and lagged wages.

Third, we consider the distribution of the benefits of growth and the role of wages in these relationships. Higher wages contribute to reduce the share of non-standard jobs and increase labour productivity through the efficiency wage effect. Again, wage dynamics have so far received little attention by the innovation literature.

Finally, the combination of the four relationships in a simultaneous model, including lags and feedback effects, provides an accurate representation of the *good jobs-high innovation* virtuous circle, that goes beyond the linear, one-directional links typically explored in the literature.

The paper is organised as follows. Section 2 deals with the model specification, section 3 presents data and methodology; results are discussed in Section 4; conclusions follow. The Appendix provides the list of sectors we investigate; the time structure of the database organised in six periods; the description of the variables used; results of a robustness check of the simultaneous model.

2. Four explorations

The four relationships we investigate are presented here in the context of the relevant research streams, considering the key determinants and defining the model that is empirically tested. In Section 4 we first test each equation separately, assessing the robustness of results also including a broader range of controls; we then carry out the simultaneous estimation with a simplified list of variables, showing that the key relationships – with lags, feedback loops and two-way links - are confirmed.

2.1 Non-standard work

The first equation in our model identifies the determinants of non-standard employment. The latter is proxied by the share of an industry's employees who are without a full-time, permanent job – having either a full-time, fixed-term temporary job, or a part-time employment (Reljic et al. 2021). By considering different forms of non-standard contractual arrangements, this variable represents a relevant indicator of the employment quality in industries, capturing the disruption of workers' learning and capabilities.

The fragmentation of labour markets and the rise of non-standard work has received considerable academic and policy interest. First, atypical forms of employment accounted for more than half of total employment growth over the last two decades in Europe (OECD, 2015). Second, they contributed to rising income inequalities associated with the gaps between standard and non-standard jobs in terms of wages, working conditions, career advancement opportunities and welfare protection (Kalleberg 2011). Third, many advanced economies that introduced labour market reforms increasing 'flexibility' and non-standard jobs have later experienced a slowdown in productivity growth; recent research has now shown that such policies have indeed contributed to lower economic performances (Lisi and Malo 2017, Lucidi and Kleinknecht 2010, Ortega and Marchante 2010).

The determinants of industry-level non-standard employment include institutional, economic and labour factors. Industrial relations studies have documented the role of institutional settings – including unionisation, labour contracts and the bargaining power of workers – in shaping the spread of non-standard jobs (Hipp et al., 2015). We consider the declining unionisation rate and expect that a greater union representation be associated to a lower share of non-standard workers in an industry.

The relevance of involuntary non-standard employment of individuals is associated to demographic, occupational and national characteristics. Green and Livanos (2017) have shown that in Europe the share is lower in the UK and Nordic countries, and higher in Mediterranean countries; non-standard jobs are disproportionately higher in some demographic groups.[1] Occupational categories also matter; their results suggest that the share of non-standard jobs is much higher in elementary occupations, while managers, professionals and associate professionals report lower shares.

We therefore include an indicator of skill as a determinant of non-standard jobs. Our main proxy is the educational attainment - the shares of university graduates and of workers with secondary education or less; we have also tested the relevance of the top and bottom occupational groups - the share of managers, professionals and technicians, and of manual workers. We expect that industries

[1] In our analysis we do not account for demographic differences (e.g. age, gender, migrant origin) due to data limitations.

with a higher share of skilled workers - university graduates or managers - have a lower presence of non-standard workers. (see OECD, 2015).

A recent literature has explored the impact of non-standard forms of work on innovation and productivity (Reljic et al. 2021), but much less is known about the reverse causality. Grande et al. (2020) found a positive impact of innovation on the composite indicator of job quality that accounts for its different dimensions (pay, intrinsic job quality, employment quality and workplace risks). Malgarini et al. (2012), using data on Italian manufacturing firms, suggested that the impact of innovation on firms' demand for temporary workers depends on the phase of the business cycle; innovating firms hire more on a permanent basis in upswings, while in downswings rely more on temporary contracts. We therefore consider the relationship that (lagged) productivity has with employment quality in industries.

Finally, wage levels are introduced; the variable we use is the percentage difference between the average wage in an industry and the average pay in the country's sector with the highest wages; this measure of relative distance locates the industry in the national labour market and we expect that the share of non-standard workers will be higher in low-paying sectors, that is in industries with a greater distance from top wages.

Considering the differences in the incidence of non-standard forms of employment across countries, we control for distinct (time-invariant) institutional settings with country fixed-effect. Moreover, we introduce a dummy for time periods, industry effects and manufacturing.

Formally, the non-standard work equation can be written as follows:

$$QNSW_{i,j,t} = \alpha_0 + \alpha_1 Union_{i,j,t-1} + \alpha_2 Skills_{i,j,t-1} + \alpha_3 \Delta LabProd_{i,j,t-1} + \alpha_4 WageDist_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \quad (1)$$

where i, j and t are indices for industry, country and time periods, respectively; μ_i stands for the industry effects that are controlled for by dummies for the Revised Pavitt classes[2]; χ_j for country fixed effect, and τ_t for the time dummies, while ε is the error term.

2.2 Product innovation

The next equation in our model is product innovation, proxied at the industry level by the number of firms that introduced new or significantly improved goods and services over the total number of firms in the industry. Product innovation is regarded as an outcome of a technology-driven competitiveness strategy, driven by R&D efforts, the level of skills and the quality of jobs.

R&D is a generally used measure of innovation input, regardless of the approach that is adopted (Griliches 1979; Dosi et al. 1990; Van Reenen 1996). We introduce a lag in order to account for the time needed for R&D results to emerge.

[2] The Revisited Pavitt taxonomy proposed by Bogliacino and Pianta (2010) defines four industry groups for manufacturing and services: Science Based, Specialised Suppliers, Scale and information intensive and Supplier Dominated. They are characterised by different technological regimes in terms of opportunities, appropriability, cumulativeness and knowledge base (Pavitt 1984). Table A1 in the Appendix reports the industries belonging to each class.

Human knowledge is essential in the innovation process and is reflected in the skills of workers; as above, we proxy them either with educational attainment or with occupational groups (lagged) variables.

However, an industry's knowledge is more than a mere sum of individual competences; organisational factors, learning by doing, the accumulation of experience and capabilities are important in driving innovation (Dosi and Nelson 2010; Lundvall 2016). We include employment quality (proxied by the share of non-standard workers) as a variable reflecting some of these processes; we expect product innovation to be higher in industries with a lower share of non-standard workers.

Formally, the product innovation equation can be written as follows:

$$\text{ProductInnov}_{i,j,t} = \beta_0 + \beta_1 \text{R\&D}_{i,j,t-1} + \beta_2 \text{Skills}_{i,j,t-1} + \beta_3 \text{NSW}_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \quad (2)$$

Details are the same ones provided for equation (1).

In addition to these key variables, we consider additional controls that are introduced in the test for the single equation in section 4.

Alongside the 'technology push', 'demand pull' is another important driver of innovation. Building of previous work (Bogliacino and Pianta 2013) the latter is proxied by the rate of change of value-added. In line with Schumpeterian literature (Schumpeter 1942), we expect product innovation to be higher in more concentrated industries, where larger firms exert greater market power; we therefore include average firm size as an additional control.

2.3 Labour productivity

The third equation in the model is labour productivity, measured as the average annual compound growth rate of value added per hour worked. The number of hours worked is a more appropriate measure of labour inputs as it accounts for differences in working time across countries and for the increasing share of part-time jobs. The key explanatory variables include fixed capital investment, product innovation, and wage growth.

Productivity increases when value added grows faster (or declines slower) than hours worked, based on different drivers. Investment expanding production capabilities is crucial for value added growth; some investment may focus on labour saving processes that reduce labour inputs with little effect on value added. Product innovation leads to new markets that expand value added even when there is no increase in labour inputs. The efficiency wage approach shows that higher wages support productivity growth as they may increase the effort of employees, decrease shirking and attract more productive workers (Akerlof and Yellen 1990, Shapiro and Stigliz 1984).[3]

The productivity equation can be written as follows:

$$\Delta \text{LabProd}_{i,j,t} = \gamma_0 + \gamma_1 \text{GFCF}_{i,j,t} + \gamma_2 \text{ ProductInnov}_{i,j,t} + \gamma_3 \Delta \text{Wages}_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \quad (3)$$

[3] In this equation we have to include the rate of change of wages, in parallel with the rate of change of labour productivity; the wage distance variable is not appropriate in this context.

Details are the same ones provided for equation (1).

In the single equation model we introduce additional controls. First, the skill level of labour employed in the industry is considered, using the shares of managers and manual workers; we expect skills to be complementary to capital investment and innovation in driving productivity.

Second, we include the relevance of non-standard jobs, building on the studies documenting its link to declining productivity growth (Ortega and Marchante 2010; Lisi and Malo 2017; Kleinknecht 2020). The argument is that greater reliance on low-paid temporary and part-time work leads firms and industries to more labour-intensive regimes with less investment and innovation, slowing down productivity dynamics.

Third, we also test whether a catching up process allows faster productivity growth in laggard countries; we calculated the percentage difference between an industry's productivity and that of the country with the highest productivity levels in the same industry (Bogliacino and Pianta 2011).

2.4 Wages

The fourth equation deals with wages. Considering the persisting large differences in wage levels across industries and countries and the very slow wage dynamics in the period we investigate, we focus on relative wages, using the percentage difference between the average wage in an industry and the average pay in the country's sector with the highest wages; this measure accounts for the conditions of national industries and labour markets.

In fact, empirical evidence suggests that wages significantly differ across industries for workers with the same characteristics - age, experience, education, occupation, gender and race (Thaler 1989; Krueger and Summers, 1988) - as a result of the structural factors associated to technological capabilities, economic performance, union presence, etc.

The main drivers of relative wages include labour productivity, product innovation and workers skills. The gains from higher productivity are distributed between wages and profits on the basis of the bargaining power of capital and labour in industries. Product innovation opens up the possibility of higher rewards for workers involved in teachnological activities and learning processes. A higher level of skills – proxied by educational attainment – is likely to be found in the industries paying top wages.

The wage distance equation can be written as follows:

$$\text{WageDist}_{i,j,t} = \delta_0 + \delta_1\, \Delta\text{LabProd}_{i,j,t-1} + \delta_2 \text{ProductInnov}_{i,j,t-1} + \delta_3\, \text{Skills}_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \tag{4}$$

Details are the same ones provided for equation (1).

In the single equation model we introduce additional controls. First, skills are also proxied by the shares of managers and manual workers, in order to assess the robustness of the relationship with wages. Second, union density is introduced to account for the institutional setting of industrial relations in industries. Third, firm size accounts for firms' market power.

2.5 The virtuous circle model

The previous subsections have explored the drivers of employment quality, innovation, productivity, and wages separately. We can now move beyond one-way relationships and combine the four equations in a simultaneous model that can summarise the *good jobs-high innovation* virtuous circle. In short, higher employment quality (and lower non-standard jobs) complements technological activities and skills, leading to more product innovations that increase productivity growth; in turn, higher productivity brings wages close to top-paying industries, improving also employment quality. The four-equation simultaneous model is shown below:

$$
\begin{aligned}
QNSW_{i,j,t} &= \alpha_0 + \alpha_1 Union_{i,j,t-1} + \alpha_2 Skills_{i,j,t-1} + \alpha_3 \Delta LabProd_{i,j,t-1} + \alpha_4 WageDist_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \\
ProductInnov_{i,j,t} &= \beta_0 + \beta_1 R\&D_{i,j,t-1} + \beta_2 Skills_{i,j,t-1} + \beta_3 NSW_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \\
\Delta LabProd_{i,j,t} &= \gamma_0 + \gamma_1 GFCF_{i,j,t} + \gamma_2 ProductInnov_{i,j,t} + \gamma_3 \Delta Wages_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t} \\
WageDist_{i,j,t} &= \delta_0 + \delta_1 \Delta LabProd_{i,j,t-1} + \delta_2 ProductInnov_{i,j,t-1} + \delta_3 Skills_{i,j,t-1} + \mu_i + \chi_j + \tau_t + \varepsilon_{i,j,t}
\end{aligned}
\tag{5}
$$

The novelties in this simultaneous model have already been pointed out in presenting individual equations. In linking the equations together, we have to pay particular attention to the feedback loops that are present and to the structure of lags that is included. Several tests of the robustness of the model have been carried out, and are discussed with the results in section 4.

3. Data and econometric strategy

3.1 Data overview

The empirical analysis uses the new version of the Sectoral Innovation Database with the NACE Rev.2 classification, which merges information on industries' economic performance from different sources, including economic data from the OECD's Structural Analysis database, innovation activity from the Community Innovation Survey (CIS), labour market variables from EU Labour Force Survey (Pianta et al. 2021). The investigation is carried out on 18 manufacturing and 23 service industries (listed in Table A1 in Appendix) of six major European economies - Germany, Spain, France, Italy, the Netherlands and the UK - over the 1994–2016 period.

The lack of annual innovation surveys led us to develop a periodical and balanced panel with six time periods corresponding to upswings and downswings of the business cycle. As shown in Table A2 of Appendix, innovation variables (sourced from six different CIS waves) were matched with economic and labour market data with lags in order to account for the time necessary for innovations to develop their economic effects.[4]

Finally, as the statistical classification of economic activities (NACE) moved from Rev. 1.1 to Rev. 2 in 2008 all data for years before 2008, expressed in terms of NACE Rev. 1.1, have been converted to NACE Rev. 2 using the conversion matrices provided by Pianta et al. (2021). Furthermore, all monetary variables have been deflated, converted to euros and adjusted for purchasing power parities to allow for cross-country comparability. The list of variables, a description of the sources, and methodology used for their construction are reported in Table A3 of Appendix, while Table A4 reports summary statistics.

[4] When lagged variables are introduced in our individual or simultaneous equations, the first period of the database is lost; as economic data are not available after 2015, in some equations the sixth period is not considered.

3.2 Econometric strategy

First, we test each equation separately, with several controls and different specifications. Second, we test the simultaneous model with the system of equations with lags and feedback effects.

With regards to the single equations, we adopt the following identification strategy. First, all specifications include country, time, and industry dummies to control for institutional, time and structural heterogeneities. Time dummies are needed to control for the business cycle and to avoid that time-specific effects, otherwise captured by the error term, may rise endogeneity concerns. As industries differ in their technological regimes, we introduce dummies for the four Revised Pavitt classes and for the manufacturing-services divide, as they account for the structural characteristics of industries while avoiding the risk of multicollinearity potentially induced by the inclusion of a large number of sector-specific dummies. In the product innovation equation dummies for technological regimes alone are included, as they properly account for heterogeneity.

Second, most explanatory variables are lagged by one period (3-4 years) in order to take into account the time required for economic effects to fully emerge in innovation processes, production systems and labour markets; this also reduces the risk of simultaneity-related endogeneity bias (Van Reenen 1996).

Third, considering that industry data are grouped data of unequal size, we use the Weighted Least Squares (WLS) estimator (Wooldridge 2002) to avoid that sector of small size and modest economic significance contribute equally to other sectors in terms of information. We use the total number of employees in industry as weights; an alternative weight would be value added, but the former is preferred as it is not affected by prices.

In the simultaneous model we estimate the system of equations using the three-stage least squares (3SLS) estimator because it allows to account for cross-equation correlation among the errors. This method estimates all coefficients simultaneously and has a relative advantage with respect to 2SLS, which estimates each equation separately[5]. In the simultaneous model we include country dummies to control for different institutional environments, a manufacturing dummy for structural differences, and time-fixed effects.

4. Results

The results of the individual equations on employment quality, product innovation, labour productivity and wage distance are presented in Tables 1-4, where different specifications with additional controls are included. The results of the simultaneous model are then shown in Table 5 and in Appendix Table A5.

4.1 Single equation models

The non-standard work equation. Table 1 shows that our model for the share of non-standard workers is supported by the empirical estimation on the industries of major European economies; two specifications are offered, all variables are significant with the expected signs. More unionised sectors

[5] When cross-equation disturbances are not correlated (which is not our case), 3SLS is equivalent to 2SLS.

have higher employment quality (and less non-standard workers), confirming the important role of unions in building an appropriate institutional setting for industrial relations. In the specification of column 2 skill levels are proxied by the shares of university graduates and employees with secondary education or less, with opposing signs; sectors with more highly educated workers have less non-standard workers. Higher productivity growth also contributes to reduce non-standard jobs, confirming previous results (Grande et. al. 2020) on the little explored link between economic performance and employment quality. In the specification of column 1 we also include product innovation, finding the expected negative relationship with non-standard workers. Finally, in both specifications the wage gap from the top-paying industry is positively associated to the relevance of non-standard work.

Product innovation. Table 2 presents the results for our model on product innovation; three specifications are offered, confirming the expectations of our model. R&D expenditure is a key driver of new products in all versions of the model, confirming widespread results (Bogliacino and Pianta 2011). Skill levels are proxied by educational levels in specifications 1 and 2, and by occupational groups in column 3; the share of university graduates always has a positive and significant effect on the ability of industries to introduce new products, while the share of workers with lower education is not significant, as they are less involved in the innovation process. In column 3 the share of managers, professionals and technicians in total employees has a positive but non significant sign, and the share of manual workers has a negative and non significant sign. In all versions of the model employment quality contributes to product innovation; the share of non-standard workers has negative and significant coefficients, in line with Reljic et al. (2021). In column 2 and 3 we introduced additional controls; firm size always has a positive and significant effect on new products, confirming the results of a large Schumpeterian literature. Conversely, the demand-pull effect, proxied by change in industries' value added, is never significant.

Labour productivity. Table 3 shows the results for labour productivity, again with three specifications of the model. Capital accumulation, proxied by gross fixed capital formation per hour worked, always has – as expected - a positive and significant effect on productivity change. Product innovation has a positive but non significant coefficient in all versions. Efficiency wages are confirmed to be a significant drivers of productivity in all equations. In columns 2 and 3 we add additional controls. The catching up effect of productivity is significant in both versions; industries that lag behind Europe's top performer are able to increase faster their hourly output, learning from and imitating other countries. Conversely, size effects turn out to be non significant. The role of labour in productivity growth is further confrmed by the role of employment quality; a higher share of non-standard workers significantly slows down productivity growth in both equations. In equation 3 we also added occupational groups as proxies of labour skills, finding that a higher share of manual workers significantly slows down productivity growth, while the share of managers has no significant effect.

Table 1. Results of the Non-standard work equation

Variables	(1)	(2)
Union density, lag	-0.350***	-0.346***
	(0.0523)	(0.0539)
% University graduates, lag		-0.178***
		(0.0587)
% Low education, lag		0.130*
		(0.0683)
Δ Labour productivity, lag	-0.314**	-0.254**
	(0.140)	(0.122)
Wage distance, lag	0.362***	0.440***
	(0.0413)	(0.0365)
% Product innovators, lag	-0.0640*	
	(0.0369)	
Country dummies	Yes	Yes
Period dummies	Yes	Yes
Pavitt dummies	Yes	Yes
Manufacturing dummy	Yes	Yes
Constant	31.51***	31.27***
	(3.611)	(3.416)
Observations	859	1,083
R-squared	0.653	0.677

Note: Weighted least squares (WLS) with robust standard errors in brackets, weights employed are sector- and time-specific number of employees.; * significant at 10%, ** significant at 5%, *** significant at 1%

Table 2. Results of the Product innovation equation

Variables	(1)	(2)	(3)
R&D expenditure, lag	1.811***	1.667***	1.755***
	(0.224)	(0.229)	(0.224)
% University graduates, lag	0.131**	0.127**	
	(0.0562)	(0.0603)	
% Low education, lag	0.0669	0.0863	
	(0.0556)	(0.0602)	
% Managers, lag			0.0565
			(0.0376)
% Manual workers, lag			-0.0374
			(0.0349)
% NSW, lag	-0.150***	-0.203***	-0.198***
	(0.0486)	(0.0735)	(0.0690)
Size, lag		3.769**	3.241**
		(1.624)	(1.568)
Δ Value added, lag		-0.0847	-0.131
		(0.143)	(0.141)
Country dummies	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Pavitt dummies	Yes	Yes	Yes
Constant	58.09***	57.97***	60.95***
	(3.398)	(3.706)	(3.500)
Observations	741	705	699
R-squared	0.734	0.736	0.737

Note: Weighted least squares (WLS) with robust standard errors in brackets, weights employed are sector- and time-specific number of employees.; * significant at 10%, ** significant at 5%, *** significant at 1%

Table 3. Results of the Labour productivity equation

Variables	(1)	(2)	(3)
Capital investment	0.0621**	0.0444*	0.0467*
	(0.0243)	(0.0246)	(0.0239)
% Product innovators	0.00795	0.00861	-0.00626
	(0.0106)	(0.0133)	(0.0159)
Δ Labour compensation, lag	0.293***	0.275***	0.257***
	(0.0891)	(0.0860)	(0.0847)
Productivity distance		0.0295**	0.0335***
		(0.0121)	(0.0123)
% NSW		-0.0415***	-0.0430***
		(0.0155)	(0.0161)
Size		-0.512	-0.173
		(0.678)	(0.698)
% Managers			-0.0238
			(0.0150)
% Manual workers			-0.0188*
			(0.0104)
Country dummies	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Pavitt dummies	No	Yes	Yes
Manufacturing dummy	Yes	No	Yes
Constant	-0.629	1.114	3.209**
	(0.900)	(1.193)	(1.426)
Observations	734	667	666
R-squared	0.138	0.185	0.208

Note: Weighted least squares (WLS) with robust standard errors in brackets, weights employed are sector- and time-specific number of employees.; * significant at 10%, ** significant at 5%, *** significant at 1%

Table 4. Results for the Wage distance equation

Variables	(1)	(2)	(3)
Δ Labour productivity, lag	-0.766***	-0.738***	-0.865***
	(0.170)	(0.159)	(0.164)
% Product innovators, lag	-0.129**	-0.177***	-0.116**
	(0.0583)	(0.0563)	(0.0586)
%University graduates, lag	-0.0456	-0.0102	
	(0.0868)	(0.0829)	
% Secondary education, lag	0.335***	0.341***	
	(0.0786)	(0.0778)	
%Managers, lag			-0.138**
			(0.0576)
%Manual workers, lag			0.0950**
			(0.0404)
Union density, lag	-0.174***	-0.146**	-0.229***
	(0.0588)	(0.0583)	(0.0651)
Size, lag		5.889***	
		(1.744)	
Country dummies	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Pavitt dummies	Yes	Yes	Yes
Manufacturing dummy	Yes	Yes	Yes
Constant	42.52***	40.26***	53.16***
	(6.035)	(5.741)	(5.345)
Observations	924	901	916
R-squared	0.574	0.587	0.567

Note: Weighted least squares (WLS) with robust standard errors in brackets, weights employed are sector- and time-specific number of employees; * significant at 10%, ** significant at 5%, *** significant at 1%

Wages. Table 4 reports the results for the wage distance equation, with three specifications of the model that confirm our expectations. The gap of an industry's wages from the top-paying sector in the country is significantly reduced by faster productivity growth in the industry, in all versions of the model. The same result is found for product innovation, as innovative success contributes to increasing labour remuneration. Moreover, in all specifications, the latter grows faster where unions are present.

Moving to different specifications of the model, we include labour skills, in column 2 with educational variables and in column 3 with occupational groups. The share of university graduates has a non-significant effect on relative wage increases, while a large share of employees with secondary degrees or less is associated to a higher distance from top wages in the economy. In columns 3 we find that the share of managers and the share of manual workers in industry employees have contrasting and significant effects, reducing and expanding – in this order - the gap from the best-paying industries. Finally in column 2 firm size is included as a control, showing a positive and significant effect on wage distance; while firm-level evidence suggests that large firms pay more than smaller ones in the same industry, at the sectoral level gaps emerge between the highest-paying knowledge-intensive services – finance, real estate and business services – where small average firm size dominates, and the labour intensive industries with lower skills where average firm size is higher.

The findings of the separate estimations of the four equations show that the model we proposed is supported by econometric results; the additional controls we introduced provide evidence of the robustness of the fundamental relationships and highlight further dimensions that contribute to these processes.

4.2 The simultaneous equation model

The simultaneous model combining the four equations on non-standard work, product innovation, productivity and wages has been estimated with three-stage least squares; the results are presented in Table 5. The simultaneous equations confirm the results of the separate estimations and are able to introduce cross-effects and feedback loops, providing a fuller, more integrated picture of the joint relationships between non-standard work, product innovation, productivity and wages.

Looking first at employment quality (column 1), we find that the share of non-standard work is reduced by unionisation and by productivity growth, while is increased by a large presence of employees with lower education and by relatively lower wages; all coefficients are significant. Conversely, the share of university educated workers is not significant.

The product innovation equation (column 2) confirms that knowledge and competences developed in R&D activities and in high labour skills are the fundamental drivers of innovation. R&D expenditure and the share of university graduates have a positive effect, while the shares of employees with lower education and of non-standard workers have negative coefficients; all are significant.

The labour productivity equation (column 3) shows that capital investment, technology and wage growth have all positive and significant coefficients. This simplified representation captures the key drivers of improved performances.[6]

[6] The product innovation variable was not significant in the results of the separate estimate of the productivity equation in Table 3; as in the previous equation, a lag is introduced for labour compensation only, due to the time required for labour market changes.

Table 5. Results of the simultaneous model of job quality, product innovation, productivity, and wages

Variables	(1) % NSW	(2) % Product innovators	(3) Δ Labour productivity	(4) % Wage distance
Union density, lag	-0.243***			
	(0.0374)			
% University graduates, lag	0.0658	0.485***		-0.0957
	(0.0483)	(0.0602)		(0.0724)
% Secondary education, lag	0.125**	-0.121*		0.482***
	(0.0556)	(0.0656)		(0.0757)
Δ Labour productivity, lag	-0.556***			-0.865***
	(0.131)			(0.183)
Wage distance, lag	0.186***			
	(0.0304)			
R&D expenditure, lag		1.529***		
		(0.179)		
% NSW, lag		-0.273***		
		(0.0521)		
Capital investment			0.0610**	
			(0.0244)	
% Product innovation			0.0240*	
			(0.0133)	
Δ Labour compensation, lag			0.215***	
			(0.0713)	
% Product innovators, lag				-0.273***
				(0.0460)
Country dummies	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Manufacturing dummy	Yes	Yes	Yes	Yes
Constant	25.98***	36.65***	-1.506**	48.88***
	(2.613)	(2.960)	(0.666)	(4.005)
Observations	495	495	495	495
R-squared	0.665	0.745	0.131	0.558

Note: Three-stage least squares, weights employed are sector- and time-specific number of employees; * significant at 10%, ** significant at 5%, *** significant at 1%

The wage distance equation (column 4) confirms that labour skills, productivity and new products shape the evolution of relative wages in industries. The distance of an industry's wages from the top-paying sector of a country is increased by a high share of employees with lower education, while the share of university graduates does not emerge as significant. Labour productivity growth and product innovation are major engines of wage convergence; all variables are lagged to allow for the time required for changes in wage setting.[7]

Taken together, we find that joint system of equations should be preferred over the single equation approach because cross-equation correlations are significant[8].

The estimation results - concerning manufacturing and service industries of major European countries - confirm the existence of a virtuous circle between employment quality, product innovation, productivity and wages. The *good jobs-high innovation* virtuous circle is rooted in the complex, positive interactions that link together the characteristics of high-quality labour – in terms of skill levels, employment contracts, unionisation, wages - and high-quality capital – considering investment, R&D, product innovation, productivity.

With our conceptual approach and econometric models we have documented four key sets of relationships. First, high employment quality is driven by employees' educational levels, unionisation, productivity and wage levels. Second, in turn, employment quality and high labour skills are combined with R&D efforts resulting in higher product innovation, the outcome of a strategy of *technologal competitiveness*. Third, in turn, product innovation, investment, and wage growth lead to greater labour productivity. Fourth, in turn, productivity gains are translated into higher wages, with labour skills and product innovation also driving up workers' pay.

5. Conclusions

Several new insights emerge from the approach we developed and the results we presented. The most important novelty is the joint consideration of the quality of labour and the quality of capital and technology as drivers of progress. Most economic research has focused on R&D, innovation and investment as engines of growth, disregarding the essential need for human labour, knowledge and learning that is behind the same R&D, innovation and production activities (Lundvall, 2016). Long term success in these directions requires both high-quality labour and higher-quality capital.

Much research has disregarded this basic fact, and has considered labour and wages simply as costs for business, that may reduce competitiveness relatively to low-wage producers in emerging countries. This narrow view of competitiveness goes hand in hand with a generic – and equally misleading - view of innovation, where no distinction is made in the types and goals of innovative

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[7] An additional simultaneous model has been estimated with three equations only, excluding wages, using the same variables; the results are in Table A5 in the Appendix. All results are confirmed; the main difference is that in the non-standard work equation also the share of university graduates becomes significant, contributing to improve employment quality. Our findings appear robust to different formulations of the simultaneous model.

[8] The 3SLS estimation method allows us to account for cross-equation correlation among errors, that we find to be significant. The Breusch-Pagan test of independence of the errors suggest that correlation coefficients are jointly significant at the 0.05 level (χ^2 = 12.608, Pr= 0.0497). The simultaneous model should be preferred over separate estimations.

activities.[9] Our results confirm the importance of the distinction between *technological competiveness*, based on the development of product innovation with high-quality labour, and *cost competitiveness*, using new processes to reduce and deskill labour (Pianta 2001). Only the former contributes to the virtuous circle that may bring sound, long-term growth.

Moving to the specific findings of this article, an important novelty is that enhancement of job quality should be seen as both the *means* and the *end* of higher innovation capabilities and higher productivity. We find that employment quality and R&D efforts are essential for successful innovation, that in turn contributes – alongside investment - to higher productivity growth, that allows higher wages which, in turn, improve working conditions by decreasing the demand for non-standard workers. This is in line with empirical studies showing that labour market flexibilisation significantly reduces productivity and discourages R&D investments, patent applications and innovation (Cetrulo et al. 2019, Kleinknecht et al. 2014, Reljic et al. 2021). However, these works have focused on the one-way relationships from non-standard employment to innovation or productivity, disregarding the reverse causality. The model used in this article allows a more integrated investigation, identifying the full role of employment quality in the *good jobs-high innovation* virtuous circle.

A further novelty concerns the inclusion of wages into the picture. In a context of stagnating incomes, we focus on wage levels relative to the top-paying industry in a country, accounting for the operation of national labour markets. We revive the notion of efficiency wage and find that higher remunerations have a key role in contributing to higher productivity growth in industries. They also support employment quality, as the share of non-standard workers falls in higher-pay sectors. Moreover, higher wages go hand in hand with higher labour skills – measured either by education or by occupational groups – in their economic effects. In contrast, industries that rely more on low wages and non-standard forms of employment may shift towards a labour-intensive, low innovation regime, with a consequent slowdown of productivity. A key lesson from our approach and results is that wage dynamics – as part of broader income distribution – is a crucial part of the explanation of economic change, including rising inequalities. For the virtuous circle of growth to operate, wages have to increase alongside the skill of workers and the quality of jobs.

Our findings are in line with many of the stylised facts of the empirical literature. The employment quality in industries increases with educational attainments, union representation and wages. Product innovation results from R&D and skilled labour. Labour productivity is driven by capital investment and product innovation. The latter also increase with larger average firm size. Wages are supported by productivity, educational levels and innovation. While these stylised facts have usually been identified in isolation from one another, we provide here an integrated approach that links them all together.

We should also point out that our analysis on manufacturing and service sectors of major European economies confirms the importance of industry-level studies. They are able to account for the dynamics of structural change, the specificities of technological regimes and labour market

[9] The use of R&D or patents as proxies for innovation complicates this problem; the use of data from innovation surveys where product innovation can be clearly identified is an important improvement in the analysis of innovation.

institutions, all aspects that can hardly be captured either by aggregate analyses on national economies or by firm-level investigations on highly heterogeneous enterprises.

Finally, our analysis also brings a policy message. We have investigated European industries in two decades of sluggish growth and stagnant wages, when the *good jobs-high innovation* virtuous circle produced modest results for the aggregate economy. Key drivers of that growth trajectory were in fact missing, with declining capital investment and worsening employment quality. Two decades of 'structural reforms' in Europe's labour markets have resulted in the large expansion of non-standard employment and in stagnant wages. This has made it possible for many small, low-productivity firms to survive in the market without improvements in technologies, organisational capabilities and labour skills, with non-standard employees largely excluded from learning processes and accumulation of competences. The quality of work and the dynamics of wages emerge from our analysis as relevant – but often disregarded - factors in explaining the performance of European industries; policies that may improve the conditions of labour appear as necessary steps for reviving the *good jobs-high innovation* virtuous circle in Europe.

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Table A1. List of sectors

Sectors (NACE Rev. 2 classification)	NACE codes	Revised Pavitt class
Manufacture of food products, beverages and tobacco products	C10-C12	SD
Manufacture of textiles, wearing apparel and leather products	C13-C15	SD
Manufacture of wood and of products of wood and cork, except furniture	C16	SD
Manufacture of paper and paper products	C17	SI
Printing and reproduction of recorded media	C18	SI
Manufacture of chemicals and chemical products	C20	SB
Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21	SB
Manufacture of rubber and plastic products	C22	SI
Manufacture of other non-metallic mineral products	C23	SI
Manufacture of basic metals	C24	SI
Manufacture of fabricated metal products, except machinery and equipment	C25	SD
Manufacture of computer, electronic and optical products	C26	SB
Manufacture of electrical equipment	C27	SS
Manufacture of machinery and equipment n.e.c.	C28	SS
Manufacture of motor vehicles, trailers and semi-trailers	C29	SI
Manufacture of other transport equipment	C30	SS
Manufacture of furniture; other manufacturing	C31-C32	SD
Repair and installation of machinery and equipment	C33	SS
Wholesale and retail trade and repair of motor vehicles and motorcycles	G45	SD
Wholesale trade, except of motor vehicles and motorcycles	G46	SD
Retail trade, except of motor vehicles and motorcycles	G47	SD
Land transport and transport via pipelines	H49	SD
Water transport	H50	SD
Air transport	H51	SD
Warehousing and support activities for transportation	H52	SD
Postal and courier activities	H53	SD
Accommodation and food service activities	I55-I56	SD
Publishing activities	J58	SI
Audiovisual and broadcasting activities	J59-J60	SI
Telecommunications	J61	SB
Computer programming, consultancy and related activities	J62-J63	SB
Financial service activities, except insurance and pension funding	K64	SI
Insurance, reinsurance and pension funding, except compulsory social security	K65	SI
Activities auxiliary to financial services and insurance activities	K66	SI
Real estate activities	L68	SS
Legal and accounting activities; management consultancy activities	M69-M70	SS
Architectural and engineering activities; technical testing and analysis	M71	SS
Scientific research and development	M72	SB
Advertising and market research	M73	SS
Other professional, scientific and technical activities; veterinary activities	M74-M75	SS
Administrative and support service activities	N	SD

Source: Pianta et al. (2021)

Note: Revised Pavitt classes: SB: Science based; SS: Specialised supplier; SI: Scale and information intensive; SD: Supplier dominated

Table A2. Time structure of the Sectoral Innovation Database Rev.2

	CIS2	CIS3	CIS4	CIS7	CIS9	CIS10
Innovation variables	1994-1996	1998-2000	2002-2004	2008-2010	2012-2014	2014-2016
Economic variables	1996-2000	2000-2003	2003-2008	2008-2012	2012-2015	x
Labour market variables	1996	2000	2003	2008	2012	2015
Inter-industry wage gap	1996	2000	2003	2008	2012	2015
Unionisation	1996	2000	2003	2008	2012	x
Capital investments	1996	2000	2003	2008	2012	2015
	First period	*Second period*	*Third period*	*Fourth period*	*Fifth period*	*Sixth period*

Economic variables and unionisation data were not available for the sixth period.
Source: Pianta et al. (2021)

Table A3. Description of variables and data sources

Variable	Description	Source
Non-standard work	Share of workers with the non-standard type of employment contract (part-time permanent, full-time temporary, part-time temporary) over the total number of employees.	EU LFS
Product innovation	Share of firms that significantly improved their goods and services in the observed period, regardless of any other type of innovation.	CIS
Labour productivity	The average annual compound rate of change of value added per hour worked	OECD-STAN
Relative wage distance	Constructed as a relative (percentage) wage distance of each sector with respect to the frontier (i.e. top-paying industry in a country), as follows: Wage distance = [(Average hourly wage$_{ij(max)t}$ - Average hourly wage$_{ijt}$)/Average hourly wage$_{ij(max)t}$] x 100	OECD-STAN
Expenditure in internal R&D	In-house research and development expenditure per employee.	CIS
Gross fixed capital formation	Investment intensity - gross fixed capital formation per hour worked.	OECD-STAN
Wage growth	The average sectoral hourly labour compensation is expressed as an average annual compound rate of change.	OECD-STAN
Size	The average number of employees is computed as a ratio between the total number of employees and firms in each sector.	CIS
Value added	Sectoral value added expressed as an average annual compound rate of change.	OECD-STAN
University graduates	Share of employees holding at least a bachelor’s degree (ISCED 6, ISCED 7, ISCED 8) over the total number of employees.	EU LFS
Low education	Share of workers with lower secondary education or below (ISCED 1, ISCED 2 and ISCED 3) over the total number of employees.	EU LFS

Managers	Share of employees in occupations ISCO1 (Managers, senior officials and legislators), ISCO2 (Professionals) and ISCO3 (Technicians and associate professionals) over the total number of employees.	EU LFS
Manual workers	Share of employees in occupations ISCO8 (Plant and machine operators and assemblers) and ISCO9 (Elementary occupations) over the total number of employees.	EU LFS
Union density	Share of workers represented by the trade union.	ICTWSS
Productivity catching-up	We calculate the cross-country distance of the labour productivity for each industry, as follows: Catching up = [(Labour productivity$_{ij(max)t}$ - Labour productivity$_{ijt}$)/ Labour productivity$_{ij(max)t}$] x 100	OECD-STAN

Source: Authors' elaboration.

Table A4. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
% Non-standard workers	20	12.95	.03	80.84
% Product innovating firms	32.27	17.15	2.1	81.82
Labour productivity growth	1.36	3.39	-10.37	13.63
Wage distance	42.26	16.61	0	77.27
Internal R&D expenditure	1.93	2.97	0	16.09
Rate of change of wages	1.02	1.75	-5.77	8.32
Rate of change of value added	.49	3.77	-10.16	15.2
Union density	23.21	11.53	6.27	58.19
Gross-fixed capital formation	7.65	7.33	.54	54.88
% University graduates	23.97	15.68	0	81.57
% Secondary education	30.87	16.46	1.38	72.46
% Managers	34.69	20.25	0	100
% Manual workers	26.75	17.63	0	74.43

Source: authors' elaboration on SID database

Table A5. The three-equation model: Non-standard work, Product innovation and Labour productivity

Variables	(1) % NSW	(2) % Product innovators	(3) Δ Labour productivity
Δ Labour productivity, lag	-0.656***		
	(0.146)		
Union density, lag	-0.358***		
	(0.0420)		
% University graduates, lag	-0.0975*	0.424***	
	(0.0531)	(0.0573)	
% Secondary education, lag	0.171***	-0.190***	
	(0.0607)	(0.0641)	
R&D expenditure, lag		1.585***	
		(0.179)	
% NSW, lag		-0.150***	
		(0.0453)	
Capital investments			0.0728***
			(0.0249)
% Product innovators			0.0253*
			(0.0149)
Δ Labour compensation, lag			0.226***
			(0.0689)
Country	Yes	Yes	Yes
Period	Yes	Yes	Yes
Manufacturing	Yes	Yes	Yes
Constant	37.84***	38.36***	-1.885***
	(2.687)	(2.869)	(0.717)
Observations	517	517	517
R-squared	0.588	0.751	0.135

Note: Three-stage least squares, weights employed are sector- and time-specific number of employees; * significant at 10%, ** significant at 5%, *** significant at 1%