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Innovations, profits and wages

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Abstract: *This paper investigates the dynamics of wages and profits and the influence innovation strategies have on them. The relationships between innovation, productivity, and distribution are modeled and estimated by employing panel data techniques. Two European innovation surveys (1994–96 and 1998–2000) are used with data at both the country and industry levels. Innovation is found to have positive effects on income dynamics beyond the role it has on productivity gains; it may weaken the distribution constraint posed by the competition between profits and wages. Profits are driven by both the Schumpeterian effects of new products and the diffusion effects of new technologies and production processes. Wages tend to grow faster in sectors where innovation expenditure is higher, but the factors affecting wages are different for high- and low-innovation sectors, suggesting that two contrasting models of technological and price competitiveness have important distributional implications.*

Key words: *distribution, innovation, profits, wages.*

The (missing) link between innovation and distribution

The analysis of the distribution effects of technological change is generally disregarded in innovation and growth studies. Still, it is a crucial element in the link between supply and demand in the process of economic development. This paper integrates the analyses of the productivity-led growth of profits and wages with a Schumpeterian perspective on the differences in innovation strategies across industries.

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Our starting point is the developments in the Post Keynesian approach—building on Kaldor (1956)—where changes in the supply structure are combined with the dynamics of demand resulting from particular distribution patterns. Distribution is addressed here in its simplest dimension—the dynamics of gross wages and profits paid in industries, disregarding the redistributive effects of taxation, public expenditure, and other policies. Changes in supply are assumed to result mainly from the patterns of technological change; building on the distinction between the introduction of *new products,* leading to temporary monopoly profits, and *new processes,* spurred on by a search for a wage bill reduction (Schumpeter, 1934), we argue that, within industries, a dominance of the former is associated to a strategy of *technological competitiveness,* and efforts to increase *price competitiveness* are behind the prevalence of process innovations (Pianta, 2001). Industries are the chosen level of analysis, as they allow us to account for countries' economic structures and productivity trajectories, and to explore the effects of specific patterns of technological change.

Technological change and distribution

The dynamics of wages and profits are, at the same time, a major determinant and a consequence of innovation.[1] Among the determinants of innovation, the search for temporary monopoly profits and the response to wage pressure are major factors inducing innovative efforts. Conversely, technological change is a major source of productivity growth that may lead to higher profits, higher wages, and lower prices. Finally, the increased demand generated by higher incomes may favor further technological and structural change.

The equilibrium perspective of neoclassical approaches hides the links between innovation and distribution behind the assumptions of price theory. Price flexibility and competition ensure that a new (unique) equilibrium with optimal wage and profit rates is reached after the introduction of new technologies, as changes in marginal productivities lead to proportional changes in factors remuneration.[2]

[1] The link between innovation and profits was at the core of Schumpeter's work (1934). A discussion of the views of Schumpeter and Penrose on innovation and profits is in Cantwell (2002). For a neo-Schumpeterian perspective, see Freeman and Louca (2001) and Perez (2002); the latter addresses the specific role of financial capital.

[2] In the more recent versions of neoclassical theory, the economic effects of innovation and technology shocks are immediately balanced across economic

Post Keynesian perspectives, building on Kaldor (1956) and Robinson (1960), have focused on the problems of distribution in economic growth. The dynamics of wages, profits, and prices—and the relative shares influenced by workers' bargaining power—have been related to the demand and supply conditions for continuing accumulation and growth. On the supply side, production capabilities are shaped by the patterns of capital investment, changes in techniques, and by varying degrees of oligopoly power that affect price and wage setting and, in turn, demand and distribution dynamics (Sylos Labini, 1967; 1979). Pasinetti (1981; 2001) argued that the growth process can proceed in a balanced manner only if the increases in the productivity potential induced by innovation are fully compensated by increases in effective demand, resulting from an appropriate distributive setup and evolving consumption patterns. These approaches suggest that technological change may lead to income polarization, inadequate demand, and underconsumption, and that technological unemployment may emerge as a consequence of changes in supply structures.[3]

Neo-Schumpeterian views, on the other hand, emphasize the sectoral specificity of technological change, which may lead to a mismatch between the emerging techno-economic paradigm and the previous social and institutional arrangements that regulate the distributive outcome (Freeman and Louca, 2001). Empirical studies on the relationship between innovation and profits have often moved from a view of profit seeking as the motivation behind investment in innovation and technology, both in industry models (Klepper, 1997) and in studies of firms (Cefis and Ciccarelli, 2005; Gerosky et al., 1993; Teece, 1986).

Concerning wages, recent literature has explored the impact of technological change on the *relative* composition of wages for high- and

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agents and sectors because price signals are at the basis of intertemporal optimization. In the real business cycle theory, because of the assumption of rational expectations equilibria, technology shocks have immediate effects on labor productivity and real wages; as long as they are perceived as temporary, they affect the expected wage rate (in this perspective conceived as the present to future real wage ratio) and thus labor supply. This, in turn, explains the positive correlation between employment and economic dynamics, leading to a "real" (technology-based) explanation of the cycle (Prescott, 1986). In the new growth theory, models with endogenous technological change and differences among firms, industries, and goods have been developed, while maintaining an equilibrium approach rooted in market-clearing processes (Aghion and Howitt, 1992).

[3] A collection of Post Keynesian perspectives on distribution is in Sawyer (1988). For an analysis of technology, growth, and employment issues, see Vivarelli (1995) and Vivarelli and Pianta (2000).

low-skilled workers (less attention has gone to *absolute* wage dynamics), focusing on the polarizing effects of innovation. Wages tend to be higher and grow faster in industries with higher technological opportunities, and for workers with higher education or using computers at work (for reviews, see Acemoglu, 2002; Chennells and Van Reenen, 2002; Pianta, 2005).

An issue that does *not* emerge in these investigations, however, is the role played by different innovation strategies. Building on the Schumpeterian distinction between *new products* and *new processes,* we argue that, in industries where the former are prevalent, a strategy of *technological competitiveness* can be identified, with firm growth driven by attempts to innovate and ascend the quality ladder to capture a stream of monopoly profits. Conversely, in sectors where new processes prevail, a strategy of *price competitiveness* emerges, with innovation introducing more efficient methods of producing existing goods. In both cases profits increase, but this is the result of different mechanisms with contrasting consequences for wages; in the former, innovation creates new value added (when adequate demand exists), while in the latter, increased productivity and profits may come at the expense of employment and wages. A strategy of *technological competitiveness* appears more likely to set in motion a cumulative growth process of increasing incomes, new demand for new products, and increased output.[4]

Investigating innovation, profits, and wages

In order to investigate the influence of specific technological strategies on wages and profits, a study at the *industry level* makes it possible to combine information on the diversity of innovation processes—rooted in firm-level decisions—and the overall distribution outcomes—usually analyzed at the macroeconomic level. An industry-level study can identify the overall effect of innovation within a sector, considering both the direct impact on innovating firms and the indirect effects on other firms.

In the analysis of innovation, the limitations of proxying technological change with research and development (R&D) or patents can now be overcome with the use of innovation surveys (European Commission-Eurostat, 2004). Two limitations, however, persist. The first limitation is the reliance on cross-sectional analyses over industries and countries

[4] See Agarwal and Audretsch (2001), Duranton (2000), Klepper (1996), Pianta (2001).

where innovation variables enter in levels. This results in the lack of dynamic evidence on the evolution of innovative activities.[5] The second is the simultaneous structure of the relations often tested, with a lack of longer time lags that may be required to allow for the full emergence of the distribution effects of innovation in industries. The availability of the second and third Community Innovation Surveys (CIS), relative to the years 1994–96 and 1998–2000, makes it possible to overcome some of these limitations (see the fourth section).

The key dynamics explored in this paper are those of the *aggregate profits* and of the *wages per worker* across industries. Although a more specific investigation of *rates of return* to capital could be more appropriate, the lack of data on industries' fixed assets makes such a study unfeasible. In most sectors, however, we can assume that the capital stock does not change rapidly (and relative differences across industries may change even more slowly); therefore, the variability of total profits appears as a good proxy for the variability of industries' returns to capital.[6]

The analysis is carried out on 11 industrial sectors and 10 European countries—Austria, Finland, France, Germany, Italy, Norway, Spain, Sweden, the Netherlands, and the United Kingdom—over the 1994–2001 period. The economic variables employed in the analysis are the following: (1) the annual rate of change (in real terms) of labor compensation per employee ($\Delta WAGE$), (2) the annual rate of change (in real terms) of gross operating surplus ($\Delta PROF$), (3) the annual rate of change (in real terms) of labor productivity (value added per employee, $\Delta PROD$), and (4) the annual rate of change (in real terms) of value added (ΔVA) (see the Appendix for further details).

The innovation indicators used are drawn from two European innovation surveys, CIS 2 (1994–1996) and CIS 3 (1998–2000). Three variables are

[5] The (static) sectoral differences have been found to be largely stable over time, due to the important differences in technological regimes and innovative strategies across industries, but only the availability of a longer series of surveys in the future will allow a fully dynamic investigation.

[6] Conversely, in the case of wage variables, the total wage bill directly depends on the number of workers and would not identify the distributive dynamics associated with innovation; the focus has to be on the growth of wages per employee, as they reflect the benefits of innovation going to workers; growing individual wages, moreover, are the key factor attracting labor in innovating industries. Finally, another way of testing the relationship between innovation and distributional dynamics is an analysis of the labor shares in industries' value added; this approach is developed in Pianta and Tancioni (2008).

considered in order to account for the diversity of innovation strategies, and their different relationships with distributional performances; they include (1) the percentage of innovating firms on total firms (*INNFIRM*), a proxy of the overall diffusion of innovation in European industries, with a dominant role of the introduction of new processes; (2) the percentage share of turnover from new or improved products (*INNTURN*), measuring the market impact of product innovations; and (3) the percentage share of innovative expenditure on turnover (*INNEXP*), a variable measuring the innovative effort, largely associated with the number of researchers and technicians involved in R&D and other innovative activities.

Descriptive evidence is provided in the Appendix. Appendix Figure A1 shows the average wage and profit dynamics and the averages of innovation variables calculated for the whole sample. Appendix Figure A2 shows the averages for countries and sectors. In addition, they show the averages for the two groups of high- and low-innovation industries.[7] The growth rate in the 1994–2001 period of aggregate profits was more than twice that of wages per worker. The average share of innovative firms on total enterprises was about 48 percent, the share of turnover due to new or improved products averages at nearly 20 percent, and the average innovative expenditure was nearly 3 percent of turnover. Considering the distinction between high- and low-innovation industries, the wage and profit dynamics in the highly innovative sectors are roughly twice as much as those in the low-innovation group. The sectors in which wage and profit growth is generally higher—chemicals and electronics in particular—are also sectors in which innovative activity is important.

This preliminary evidence shows that, across industries, a greater innovativeness may be correlated with higher wage and profit growth; in particular, a higher wage dynamic is observed where the shares of innovative expenditure and innovated turnover are higher; this may suggest that wage increases are easier in industries with large innovative capacities and highly skilled R&D personnel.

[7] High- and low-innovation sectors are defined on the basis of their values in the innovation variables considered. Low-innovation industries include food, beverages, and tobacco; textiles and leather; wood, pulp, and publishing; basic and fabricated metals; manufacturing NEC (not elsewhere classified) and recycling. High-innovation sectors include coke and chemicals; rubber, other nonmetallic products; machinery and equipment; electrical and optical equipment; and transport equipment. The electricity, gas, and water supply sector has not been included in the high–low innovation grouping.

The model

The neoclassical approach explains income distribution within price theory. Wage and profit equations can be analytically derived by assuming a constant returns to scale production technology employing labor and capital. Under the assumption of perfect competition, factor remunerations equal marginal productivities and define the relative shares in total production (Foley and Michl, 1999). We challenge this perspective by focusing on the role of labor productivity in sustaining the growth of wages and profits, and by considering the role of the innovative variables described in the previous section. Moreover, we include the profit and labor income dynamics in, respectively, the wage and profit equations in order to capture the role of the bargaining process over distribution. The resulting empirical specifications are the following:

$$\Delta WAGE = f(\Delta PROD, \Delta PROF, INNFIRM, INNTURN, INNEXP) \quad (1)$$

$$\Delta PROF = f(\Delta PROD, \Delta WAGE, INNFIRM, INNTURN, INNEXP). \quad (2)$$

Even if the small time dimension makes the issue of nonstationary variables less important, the risk of spurious results is eliminated by taking logarithms and differencing. The consideration of approximated growth rates for labor compensation ($\Delta WAGE$), gross profits ($\Delta PROF$), labor productivity ($\Delta PROD$), and of stationary ratios imply that the equations are balanced in terms of the statistical properties of the variables being employed.[8]

The database includes information on three dimensions—sectors of economic activity i (industries), countries j, and time t. Given the reduced time span for which data are available (1994–2000), our estimation framework is necessarily the standard panel estimator for T-small, N-large. The empirical strategy is developed in three subsequent stages, briefly described in the next section.

We expect to find a relevant and positive relationship of both wages and profits with productivity growth that captures the *realized* economic effects of improved production conditions. Moreover, we expect different relationships with the innovative measures associated with specific innovation strategies. As the share of innovative firms proxies the general

[8] In order to check the robustness of our profit equation estimates, we tested an alternative formulation in which the growth of labor productivity (value added per worker) is replaced by the growth of aggregate value added; see Table A2 in the Appendix.

diffusion of innovation, with a strong presence of new processes, we can expect a negative association to wage dynamics due to the possibility of restructuring and job reduction strategies. Conversely, as the share of innovated turnover and the importance of innovation expenditure proxy strategies of *technological competitiveness* with a major role of product innovation, we may expect that improved labor demand conditions may lead to a more positive effect on wages. We also expect to obtain a negative relationship of both income components with the respective counterparts, because the real-world wage determination is a bargaining process that is unlikely to satisfy the predictions of the general equilibrium theory.

A final relevant issue is the potential outcome of controlling sector or country effects. As long as data variability is explained by sectoral or country differences, the signs and statistical significance of the estimated coefficients may be seriously affected. Hence, the use of sectional identifiers for the particular cross section of interest is expected to give precious information on the heterogeneity of the processes which is relevant to income distribution. On the basis of these arguments, a two-groups (high- and low-innovative sectors) seemingly unrelated regression (SUR) estimation is also implemented. This represents a simple and potentially powerful tool for the evaluation of the considerations made above.

The econometric strategy

The cross-sectional evidence is explored through three different perspectives. First, an estimate of the wage and profit equations in the two subperiods 1994–1997 and 1998–2001 has been executed in order to evaluate the stability over time of the estimates. Second, the relevance of country-specific and sector-specific effects is tested to evaluate the viability of pooling the two cross-sectional dimensions. This is done by employing a two-step procedure: first the statistical relevance of the pooled against the random effects model is evaluated and then, if the random effects specification has to be chosen, the random effects model is tested against the fixed effects model.

The random effects model assumes a random sectional characterization (even if fixed over time). More specifically, in the random effects model the error is decomposed into a noisy i.i.d. (identically and independently distributed) ε component and a section-specific u component.[9]

[9] The random effects are thus fixed over time in the standard case while they are constant over time and over the group-specific section in this three-dimensional case.

$$y_{i,j,t} = a + \beta \mathbf{x}_{i,j,t} + u_{i(j),t} + \varepsilon_{i,j,t}, \tag{3}$$

where y is the dependent variable (labor income or profits), a is the constant term, $\boldsymbol{\beta}$ is the vector of the slope coefficients, and $\mathbf{x}$ is the vector of explanatory variables described in the previous section; i (j) = 1, ..., M (N) defines the specific sector (country).

The fixed effects model assumes that the section-specific effects on the dependent variables can be captured by heterogeneous constant terms only, in other words by dummies operating as intercept shifters of the linear relations:

$$y_{i,j,t} = a_{i(j)} + \beta \mathbf{x}_{i,j,t} + \varepsilon_{i,j,t}. \tag{4}$$

The two-step procedure is implemented by testing, via the Breush–Pagan Lagrange multiplier (LM) test, the absence of section-specific effects—that is, the pooled model—against the presence of sectional effects estimator, and then for orthogonal individual effects—that is, the random effects specification—with the fixed effects model as alternative hypothesis. In this second step, the reference evaluation tool is the Hausman test. Appendix Table A1 shows the results of these tests.

The Breush–Pagan test does not reject the null hypothesis for both the wage and profit specifications, irrespective of the particular sectional control being considered (sector or country). On the basis of these results, the second battery of Hausman tests has not been performed. We conclude that the pooled estimator is the appropriate one in a first specification of the model.

A usual problem in model estimation is the presence of endogenous regressors and measurement errors. In these cases, the condition of orthogonality between regressors and errors is violated, the ordinary least squares (OLS) estimator is inconsistent, and an instrumental variables (IV) estimator has to be preferred. We assume that endogeneity, if any, may affect incomes (profit growth in the wage equation and wage growth in the profit equation), value added, and productivity growth only, on the grounds that measurement errors are more likely to emerge from national account aggregates. We thus implement these variables by employing the growth rates of value added (for productivity in the wage equation), productivity (for value added in the alternative formulation of the profit equation whose results are shown in the Appendix), exports, and employment as explanatory variables in the auxiliary regressions.

In a second specification, the information is organized in order to identify two industry groups, according to the sectoral degree of innovativeness. In this case, we employ an SUR estimator in order to allow for the presence of correlation between the two sectional dimensions considered in the analysis. This modification allows a more detailed investigation and more efficient estimates; by reducing the number of the sectional controls (or increasing degrees of freedom), it enables the estimation of group-specific slope coefficients, thus the relaxation of the fixed effects–random effects hypotheses. Formally,

$$y_{i,j,t} = a_g + \beta_g x_{i,j,t} + \varepsilon_{i,j,t}, \tag{5}$$

where g indexes the high/low-innovative groups.

Results

Following on from the above strategy, we limit our discussion to the results obtained in the pooled estimates, shown in Table 1, combining countries, sectors, and periods. Separate regressions for the two periods have in fact confirmed the stability of the relationships discussed here. Appendix Table A2 reports the estimation results (Pool-IV and SUR) obtained by employing value added in the place of productivity as explanatory variable.

The growth of wages and profits appears to be closely and significantly related to productivity gains, and inversely related to their distributive complements; in the sectors and countries where profits grow faster, wages lag behind, and vice versa. Results are not changed qualitatively if value added replaces productivity in the profit equation (see Appendix Table A2). These results confirm the key role of productivity growth as the precondition for increases in all incomes, and the conflictual nature of the functional distribution between profits and wages, where institutions, bargaining rules, and social processes affect specific outcomes.

The effects of innovative efforts, however, are not entirely accounted for by the productivity performance. The three variables we considered highlight different dimensions of technological activities that have asymmetric effects on distribution. We find a positive and strongly significant effect of the share of innovative firms in the profit growth equation only, but the same variable turns out negative and statistically insignificant in the wage equation.

The share of innovation-related sales reflects the economic impact of new products, leading to higher value added and productivity, whose gains are at the root of Schumpeterian profits, but may also be shared by wages in oligopolistic industries with unionized labor (Sylos Labini, 1967). Results show that the share of innovation-related sales, even though positive in both equations, is significant for profit growth only,

Table 1
Results from pooled model estimates

Equation	Model	Model statistics	Explanatory variable	Value	Standard error
Δ*WAGE*	Pooled-IV	Adjusted R^2: 0.63	*CONSTANT*	–0.387	0.530
		$F(5, 136) = 49.69$ (0.000)	Δ*PROF*	–0.115**	0.017
			Δ*PROD*	0.775**	0.058
			INNFIRM	–0.001	0.012
			INNTURN	0.021	0.017
			INNEXP	0.159*	0.078
Δ*PROF*	Pooled-IV	Adjusted R^2: 0.47	*CONSTANT*	–8.127**	2.223
		$F(5, 136) = 26.34$ (0.000)	Δ*WAGE*	–2.201**	0.324
			Δ*PROD*	2.845**	0.300
			INNFIRM	0.144**	0.052
			INNTURN	0.154*	0.071
			INNEXP	–0.328	0.345

Notes: IV = instrumental variables estimation (instrumented variables are Δ*PROD* and Δ*PROF* in the wage equation, Δ*PROD* and Δ*WAGE* in the profit equation. Instruments are rates of change in value added, rates of change in employment and rates of change in exports). *, and ** indicate, respectively, 5 percent, and 1 percent significance levels.

confirming the relevance of temporary monopoly profits for product innovators.

Total innovation expenditures are largely accounted for by the relatively high wages of highly skilled workers (researchers and technicians) in the sectors and countries where high competence is crucial. They may attract a greater supply of qualified labor and show higher relative wages compared to low-innovation sectors, whose faster growth may be associated, in the short term, to lower increases of profits. This is what emerges from the pooled model estimates, with a positive and significant relationship between the intensity of innovation expenditure on turnover and wage growth, and a negative and insignificant relationship with profit growth.

All of these factors lead to differentiated patterns of innovation-related income growth. Wages increase faster in the sectors and countries where innovation expenditures are higher (and have no effect on profits); the general diffusion of innovation and new processes increase profits and may lead to slower wage dynamics through adverse labor market effects; and the success of new product sales accelerates the growth of Schumpeterian profits, with no effects on wages.

Table 2 shows the results of the heterogeneous panel SUR estimates obtained by distinguishing high- and low-innovation industries (see the Appendix). Separate coefficients for the two groups of industries are reported only when the difference in the estimates for the two groups of industries is significant.

Although the profit equation does not show important differences between the two groups of sectors, major differences are found for wages. In the case of profits, the differentiation is in the intercept rather than in the slope of the regression, with high-innovation sectors associated with higher profits; both the economic and the innovation variables confirm the results discussed above. In the case of wages, productivity coefficients are not significantly different in the two groups of industries, and the intensity of innovation expenditure loses its significance. Profits have two highly significant negative coefficients, and the negative link is greater in the case of low-innovation industries, where the capital–labor conflict is closer to a zero-sum game than in the sectors where higher technological activities allow for greater margins for redistribution to wages of part of the surplus.

Innovation variables have different effects on wage growth in the two groups of industries. In low-innovation industries, wages are (weakly) positively influenced by general innovation efforts, and negatively affected by the share of new products in sales; in these industries, dominated

Table 2
Results from SUR estimates

Equation	Model	Model statistics	Explanatory variable	Value	Standard error
Δ*WAGE*	SUR	Adjusted R^2: 0.71	Δ*PROD*	0.778***	0.060
(cluster HI–LOW)		Wald eq. (F): 3.70 (0.004)	*INNEXP*	0.114	0.079
		Wald eq. (χ^2): 18.54 (0.002)	Δ*PROF_L*	–0.124***	0.020
			Δ*PROF_H*	–0.081***	0.019
			INNFIRM_L	0.017**	0.009
			INNFIRM_H	–0.025***	0.010
			INNTURN_L	–0.048**	0.022
			INNTURN_H	0.054***	0.019
Δ*PROF*	SUR	Adjusted R^2: 0.48	*CONSTANT_H*	–6.798***	2.468
(cluster HI–LOW)		Wald eq. (F): 1.14 (0.343)	*CONSTANT_L*	–6.374*	3.443
		Wald eq. (χ^2): 5.70 (0.337)	Δ*WAGE*	–2.338***	0.380
			Δ*PROD*	3.268***	0.347
			INNFIRM	0.124**	0.056
			INNTURN	0.142*	0.074
			INNEXP	–0.504	0.379

Notes: SUR = heterogeneous panel seemingly unrelated regression equations. Wald equality test statistics evaluate whether the estimated coefficients for the HI/LOW innovative groups (respectively identified with _H and _L) are statistically equivalent. *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance levels.

by a strategy of *price competitiveness,* the success of efforts aimed at increasing production efficiency appears as a modest driver of wage increases. Conversely, in high-innovation industries, a large presence of new products in sales makes a faster growth of wages possible, while negative effects are found for the general innovation variable; in this case, the success of efforts at *technological competitiveness* drives wage growth.

These findings highlight important differences in the relationships between innovation and distribution, identifying specific influences of alternative technological strategies in high- and low-innovation industries. The fact that the evidence used here is basically cross-sectional does not allow, however, a detailed analysis of the particular transmission mechanisms activated by innovative efforts.

Conclusions

The results we obtained highlight four main issues. First, the conflictual distribution between profits and wages emerges as a strong force in the evolution of both types of income. Second, even if both profits and wages grow on the basis of increases in labor productivity, specific innovation strategies play a role in supporting income growth *beyond* their contribution to productivity; in this way, innovation makes the distributive race less stringent, allowing room for growth of *both* wages and profits. Third, wages tend to grow faster in the sectors where innovation expenditure (largely due to wages for high-skilled researchers and technicians) is higher, while profits are driven both by the Schumpeterian mechanism relying on the importance of new products and market power, and by the restructuring mechanism based on the diffusion of new processes and wage-depressing job reductions. Fourth, when we look separately at high- and low-innovation industries, the two parallel mechanisms of profit growth do not change significantly—although they are, on average, higher in high-innovation industries—while wages appear to be driven by the specific model of *technological* or *price competitiveness* that characterizes, respectively, the high- and low-innovation groups.

In addition to productivity growth, the mechanisms that link innovative activities to wages and profits are likely to include the importance of workers' knowledge and competence in high-innovation industries; the contrasting labor market effects of new products and new processes; the dynamics of demand that may allow for faster growth of both incomes in expanding industries. Moreover, the impact of innovation on the rate of growth of total industry profits may reflect, to some extent, changes in the capital stock over the period investigated. As the capital stock increases, given a uniform rate of return on capital, the amount of profits should rise. The lack of adequate sectoral data on fixed assets has prevented us from disentangling the effects of increases in capital and in operating surplus; therefore, a part of the "Schumpeterian effects" we found for innovation may be related to the faster pace of capital accumulation in high-innovation industries.

These insights into the complex links between the variety of innovative efforts and distributional outcomes may lead to several developments. Our models and empirical results are based on a cross section of manufacturing industries in two periods (the mid and late 1990s), with a limited dynamic comparison. The relationship between innovation and distribution would require a fully dynamic investigation, as high profits may contribute to finance innovative activities and high wages may turn into demand for innovative products. Moreover, higher wages can reflect the evolution of the economy toward more innovative, high-skill activities. In order to address these questions, a dynamic analysis is carried out in a parallel paper covering a longer time span and service industries as well as manufacturing (Pianta and Tancioni, 2007).

Three main policy indications can be drawn from our results. First, the findings show that innovation (preferably in products associated to expanding markets) can provide room for expansion of both wages and profits. A strategy for productivity, innovation-based growth, and *technological competitiveness* may bring great benefits, as it weakens the constraints that, in European countries characterized by slow growth, have turned distribution into a zero-sum game between wages and profits.

A second indication concerns the importance of industry differences. We found that sectoral regularities in innovation and income dynamics are strong and persistent; low-innovation industries in Europe are frequently associated with a stagnation (or fall) in wages and profits. Policy should recognize these simple facts and move toward selective industrial and innovation policies favoring structural change, the expansion of more dynamic sectors, and a strategy of *technological competitiveness* aimed at the development of new knowledge, competence, products, and markets.

A final indication is that large benefits can be expected from a closer integration between the supply-side, industry-based view of innovation policy and the macroeconomic, demand-side view of incomes and distribution policy.

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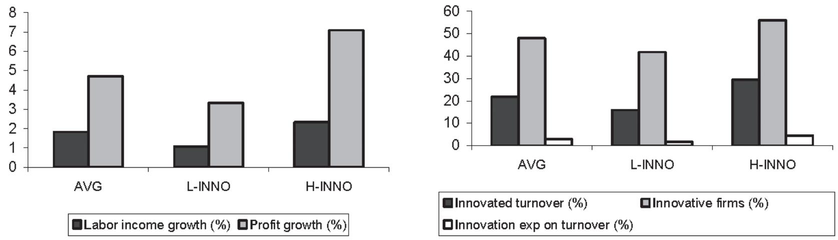
Appendix: data definitions and sources

Data used come from the Sectoral Innovation Database developed at the University of Urbino. Innovation indicators are drawn from European Community Innovation Surveys CIS 2 (1994–96) and CIS 3 (1998–2000); economic data are drawn from the Organization for Economic Cooperation and Development (OECD) Structural Analysis (STAN) database, for 11 industrial sectors—Nomenclature des activitées économiques (NACE) Revision 1 subsections—and for 10 European countries—Austria, Germany, France, Italy, Norway, Finland, Spain, Sweden, the Netherlands, and the United Kingdom—over the 1994–2001 period. The sectors were split between "high" and "low" innovation sectors on the basis of the average values of the innovation variables considered. The list of sectors is as follows.

Low-innovation industries: food and beverages (NACE Revision 1 sectors 15–16); textiles, apparel, and leather (17–19); wood, pulp, paper, and publishing–printing (20–22); basic metals and fabricated metal products (27–28); manufacturing NEC and recycling (36–37). *High-innovation industries:* coke and refined petroleum products and chemicals (23–24); rubber and plastics products and other nonmetallic mineral products (25–26); machinery and equipment (29); office, accounting and computing machinery, electrical machinery telecommunications and medical, precision and optical instruments (30–33); motor vehicles and other transport equipment (34–35). The sector electricity, gas, and water supply (40–41) has been left out in the split between high- and low-innovation industries.

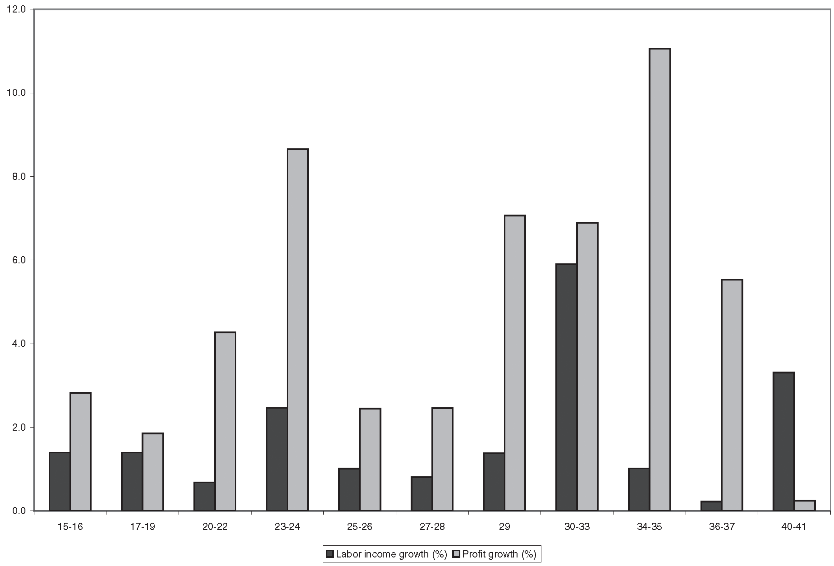
Figure A1 Average profit and labor income growth and innovation, innovative clusters

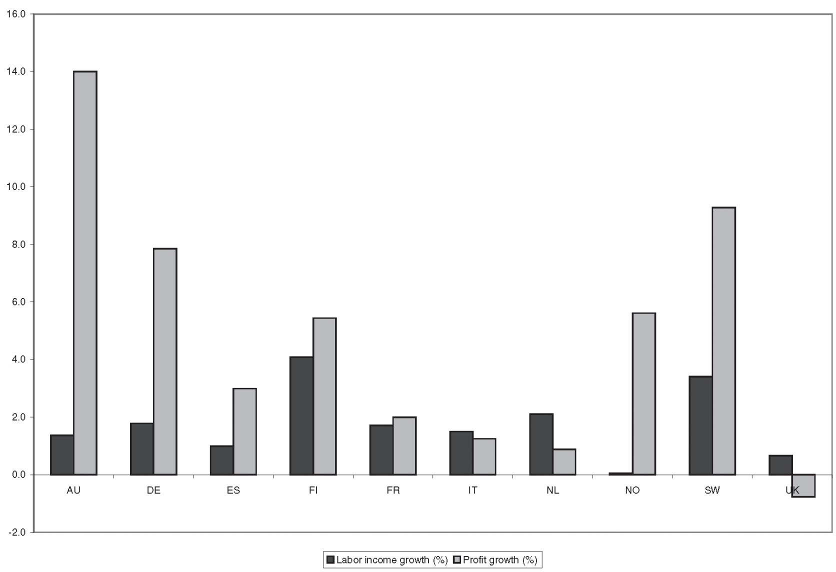


The innovation indicators. The three innovation indicators include the percentage of innovative firms in total firms with reference to the periods 1994–96 and 1998–2000; the share of turnover due to new or improved products in 1996 and 2000; the innovation expenditure to turnover ratio. The innovation variables in the two periods are based on the same definitions; the major difference between the two innovation surveys is that in CIS 2 firms, over 20 employees were surveyed, and in CIS 3, the coverage was extended to all enterprises with at least 10 employees. The patterns of these variables by high- and low-innovation clusters are shown in Figure A1; the patterns for industries and countries are shown in Figure A2.

The economic indicators. The economic indicators calculated for each country and sector considered include the annual rate of change of productivity, measured as value added per employee, obtained using the percent log of first differences approximation; the annual rate of change of labor compensation per employee, including social contributions, obtained as above; and the annual rate of change of gross operating surplus, obtained as above. The patterns of wages and profits by high- and low-innovation clusters are shown in Figure A1; the patterns for industries and countries are shown in Figure A2. Data on employment are expressed as total employment, number engaged. These figures consider one job as one worker, and they may overestimate the real number of hours worked, but they are internationally comparable. Data on total employment, full-time equivalents that account for part-time jobs are not always available across countries. Data on labor compensation were preferred to those on wages because the former also include social contributions paid by firms which represent an important part of total labor costs. Value-added data were deflated with sectoral deflators (elaborated from the OECD STAN database), and gross domestic product deflators were used to

Figure A2 Average profit and labor income growth and innovation, by sectors and countries





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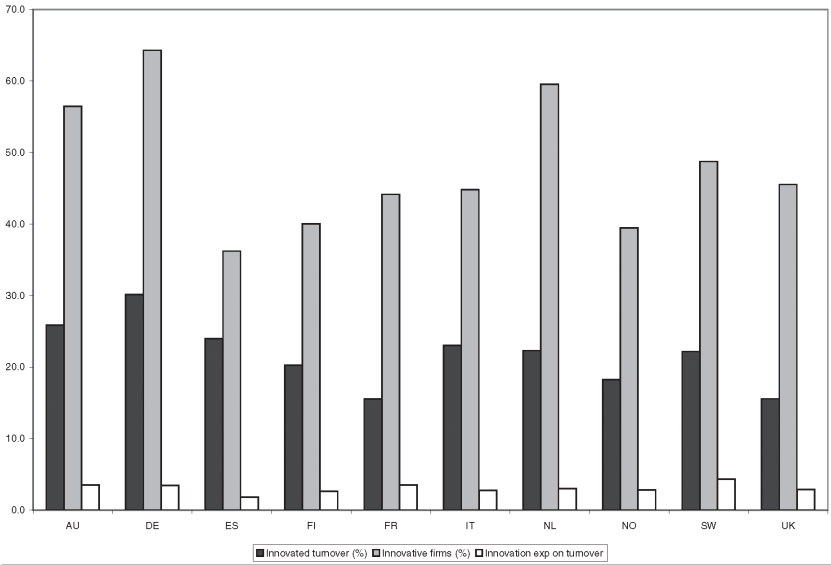

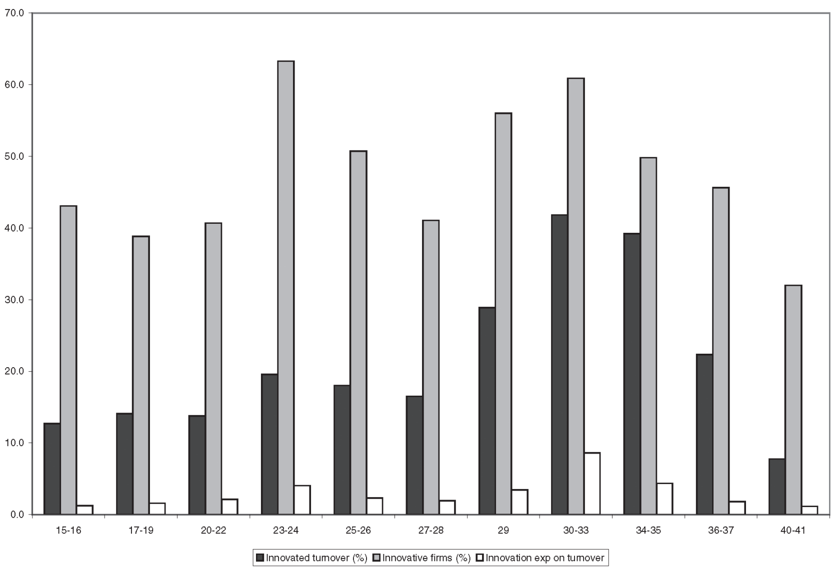

Notes: 11-sector NACE classification: 15–16: food products, beverages, and tobacco; 17–19: textiles and leather; 20–22: wood, pulp, paper, and publishing–printing; 23–24: coke and chemicals; 25–26: rubber and other nonmetallic; 27–28: basic metals and fabricated metal products; 29: machinery and equipment; 30–33: electrical and optical equipment; 34–35: transport equipment; 36–37: manufacturing NEC and recycling; 40–41: electricity, gas, and water supply. AU = Austria; DE = Germany; ES = Spain; FI = Finland; FR = France; IT = Italy; NL = Netherlands; NO = Norway; SW = Sweden; UK = United Kingdom.

Table A1
Model selection: the two-step Breush–Pagan and Hausman tests procedure

Step	Equation	Grouping	Test	Hypotheses	χ^2 (5)	p	Selected
1	$\Delta WAGE$	Country	Breush–Pagan	H0: Pool; H1: RE	1.75	0.186	Pool
1	$\Delta PROF$	Country	Breush–Pagan	H0: Pool; H1: RE	0.46	0.497	Pool
1	$\Delta WAGE$	Sector	Breush–Pagan	H0: Pool; H1: RE	2.49	0.115	Pool
1	$\Delta PROF$	Sector	Breush–Pagan	H0: Pool; H1: RE	3.27	0.071	Pool

Note: RE = random effects.

Table A2
Results from pooled model estimates

Equation	Model	Model statistics	Explanatory variable	Value	Standard error
$\Delta PROF$	Pooled-IV	Adjusted R^2: 0.47	*CONSTANT*	–5.776**	2.501
		$F(5, 136) = 26.34$ (0.000)	$\Delta WAGE$	–1.098***	0.306
			ΔVA	1.810***	0.268
			INNFIRM	0.154***	0.058
			INNTURN	0.143**	0.071
			INNEXP	–0.546	0.386
$\Delta PROF$	SUR	Adjusted R^2: 0.48	*CONSTANT_H*	–4.918***	1.968
(cluster HI–LOW)		Wald eq. (F): 1.14 (0.343)	*CONSTANT_L*	–4.352*	2.343
		Wald eq. (χ^2): 5.70 (0.337)	$\Delta WAGE$	–1.002***	0.245
			ΔVA	1.925***	0.252
			INNFIRM	0.128**	0.056
			INNTURN	0.142*	0.074
			INNEXP	–0.525	0.369

Notes: IV = instrumental variables estimation (instrumented variables are ΔVA and $\Delta WAGE$. Instruments are rates of change in productivity, rates of change in employment, and rates of change in exports); SUR = heterogeneous panel seemingly unrelated regression equations. Wald equality test statistics evaluate whether the estimated coefficients for the HI/LOW innovative groups (respectively identified with _H and _L) are statistically equivalent. *, **, and *** indicate, respectively, 10 percent, 5 percent, and 1 percent significance levels.

deflate labor compensation and profit data. The rates of change were computed for each variable for the 1994–97 and 1998–2001 periods in order to analyze the average dynamics in two different periods, as well as for the overall 1994–2001 period. Due to missing data, data on value added refer to 2000 in the case of Sweden; data on labor compensation per employee refer to 2000 in the case of the United Kingdom, Norway, and Spain and to 1999 for Sweden.